

CEP Discussion Paper No 1411

March 2016

International Competition and Labor Market Adjustment

João Paulo Pessoa

Abstract

How does welfare change in the short- and long-run in high wage countries when integrating with low wage economies like China? Even if consumers benefit from lower prices, there can be significant welfare losses from increases in unemployment and lower wages. I construct a dynamic multi-sector-country Ricardian trade model that incorporates both search frictions and labor mobility frictions. I then structurally estimate this model using cross-country sector-level data and quantify both the potential losses to workers and benefits to consumers arising from China's integration into the global economy. I find that overall welfare increases in northern economies, both in the transition period and in the new steady state equilibrium. In import competing sectors, however, workers bear a costly transition, experiencing lower wages and a rise in unemployment. I validate the micro implications of the model using employer-employee panel data.

Keywords: trade, unemployment, earnings, China
JEL codes: F16; J62; J64

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

I am grateful to John Van Reenen, Gianmarco Ottaviano and Emanuel Ornelas for their guidance and support. I am also thankful to Alan Manning, Andy Feng, Catherine Thomas, Chris Pissarides, Claudia Steinwender, Clément Malgouyres, Daniel Junior, Daniela Scur, David Dorn, Francisco Costa, Frank Pisch, Jason Garred, John Morrow, Jonathan Colmer, Katalin Szemeredi, Markus Riegler, Mirko Draca, Oriol Carreras, Pedro Souza, Steve Machin, Steve Pischke, Stephen Redding, Tatiana Surovtseva, Thomas Sampson and seminar participants at LSE, EGIT Research Meeting, IAB Spatial LM Workshop, TADC, CEP Annual Conference, Erasmus University Rotterdam, Bocconi University, FED Board, UC Boulder, PUC-Rio, FGV-EESP, FGV-EPGE, INSPER, FEA-USP, SBE Meeting and RIDGE Workshop. All remaining errors are mine.

João Paulo Pessoa, FGV-Sao Paulo School of Economics and Associate at Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system or transmitted in any form or by any means without the prior permission in writing of the publisher nor be issued to the public or circulated in any form other than that in which it is published.

Requests for permission to reproduce any article or part of the Working Paper should be sent to the editor at the above address.

© J.P. Pessoa, submitted 2016.

1 Introduction

It has been recognized that trade openness is likely to be welfare improving in the long-run, by decreasing prices and allowing countries to expand their production to new markets. These gains, however, generally neglect important labor market aspects that take place during the adjustment process, such as displacement of workers in sectors harmed by import competition and the fact that workers do not move immediately to growing exporting sectors.

In the last decades China has emerged as powerful player in international trade. In 2013, it surpassed the United States (US) to become the world's largest goods trader in value terms. In this paper I study how countries adjust to the rise of China in a world with imperfect labor markets.

The main contribution of this paper is to provide a tractable framework to structurally quantify the impact of trade shocks in a world with both search frictions and labor mobility frictions between sectors. I calculate changes in real income per capita arising from the emergence of China using numerical methods, both in the new equilibrium and along the transition period. My calculations take into account not only the benefits but also account for potential costs linked to labor market adjustments. I find that China's integration generate gains worldwide also in the short-run. However, there are winners and losers in the labor market.

My dynamic trade model incorporates search and matching frictions from [Pissarides \(2000\)](#) into a multi-country-sector [Costinot, Donaldson, and Komunjer \(2012\)](#) framework.¹ In this set-up goods can be purchased at home, but consumers will pay the least-cost around the world accounting for trade costs. Hence, individuals benefit from more trade integration by accessing imported goods at lower costs. On the other hand, a rise in import competition in a sector will decrease nominal wages and increase job destruction in this sector. Wages will not be equal across sectors within countries because of labor mobility frictions, which are added to the model assuming that workers have exogenous preferences over sectors. To analyze how all these effects interact following a trade shock I use numerical simulations.

The “China shock” used in my numerical exercise consists of a decrease in Chinese trade barriers and an increase in Chinese productivity that emulates the growth rate of

¹This is a multi-sector version of [Eaton and Kortum \(2002\)](#) where labor is the solely factor of production.

China's share of world exports following China's entry to the WTO. I find that northern economies gain from this shock. For example, annual real consumption in the US and in the United Kingdom (UK) increase by 1.3% and 2.3%, respectively, in the new steady state compared to the initial one.

The effects of the shock on wages and unemployment are heterogeneous across sectors within countries. In low-tech manufacturing industries in the UK and in the US, which face severe import competition from China, workers' real wages fall and unemployment rises. The fall in the real average wage in this sector is approximately 1.6% in the US and 0.7% in the UK during the adjustment period five years after the shock. However, at the same point in time workers in the service sector experience a rise in the real average wage and no significant change in the unemployment rate: The real average wage in services increases by approximately 1.9% in the US and 2.5% in the UK.

The numerical exercise also demonstrates the dynamic effects associated with the rise of China. Immediately after the shock, nominal wages rise in exporting sectors and fall in industries facing fierce import competition from China. As workers move from sectors hit badly by China in search of better paid jobs in other industries, wages in exporting sectors start to fall due to a rise in labor supply. This implies that wages are lower in the final steady state than during the transition in these industries. In some import competing sectors, however, the effects go in the opposite direction: Wages fall immediately after the shock and recover over time.²

In order to perform counterfactual analysis I estimate a sub-set of the parameters of the model using country-sector level data. I estimate a gravity equation delivered by the model using data on bilateral trade flows to obtain the trade elasticity parameter. I also use equations from my theoretical framework to estimate the parameters related to job destruction and labor mobility frictions between sectors. The remaining parameters are either calibrated or taken from the literature.

Even though countries experience overall real income gains in my counterfactual exercise, workers in import competing sectors lose from a fall in real wages and an increase in unemployment not only during the transition but also in the new steady state. Another prediction from my model is that low-paid (low-productivity) jobs are the ones

²More precisely, in the low-tech manufacturing sector, wages fall during the first five years after the shock in the US and during the first six years in the UK before starting to recover. Note also that wages in import competing sectors hit badly by China will still be lower in the new steady state than in the initial one.

destroyed in sectors that experience a negative shock. I validate the qualitative predictions discussed above by drawing on detailed employer-employee panel data from one developed mid-size economy, the UK. Quantitative trade exercises usually focus on the US. I also look at the US in my counterfactuals, but as a very large and rich country, I find it useful to validate the micro implications of my model on a smaller and more open economy, the UK.

By analyzing the period between 2000 (the year before China entered into the WTO) and 2007 (the year before the “Great Recession”) I provide support for the three main predictions discussed, i.e., that more Chinese import competition in an industry: i) decrease worker’s earnings; ii) increase worker’s number of years spent out of employment; iii) has a stronger impact on low-paid workers.³

I find that workers initially employed in industries that suffered from high levels of import exposure to Chinese products between 2000 and 2007 earned less and spent more time out of employment when compared to individuals that were in industries less affected by imports from China. I find a negative and significant effects in terms of both weekly and hourly earnings, and that workers that received lower wages between 1997 and 2000 (a proxy for skills) experienced higher subsequent employment losses between 2000 and 2007.

Many other papers study the effects of trade openness on labor markets by quantifying theoretical models. However, to my knowledge this is the first paper that explicitly quantifies the effects of a trade shock, the emergence of China, analyzing all the following aspects: general equilibrium effects across countries, the dynamic adjustment path to a new equilibrium (in a set-up where jobs can be endogenously destroyed) and labor mobility frictions between sectors.⁴

³My empirical strategy builds on Autor, Dorn, Hanson, and Song (2014).

⁴Caliendo, Dvorkin, and Parro (2015) develop a dynamic trade model with full employment that takes into account labor mobility frictions, goods mobility frictions, geographic factors and input-output linkages. They calibrate the model to 22 sectors, 38 countries and 50 states in the US to quantify the effects of the China shock. They find that China was responsible for the destruction of thousands of jobs in manufacturing in the US, but the shock generated aggregate welfare gains. di Giovanni, Levchenko, and Zhang (2014) evaluate the welfare impact of China’s integration considering a multi-sector, multi-country framework and also find that welfare increase in developed economies. Levchenko and Zhang (2013) study not only the aggregate but also the distributional impacts of the trade integration of China and other developing economies considering factor immobility, finding that reallocation of factors across sectors contributes relatively little for aggregate gains, but has large distributional impacts. Both papers, however, consider a static framework with full-employment. Bloom, Romer, Terry, and Reenen (2014) use a dynamic “trapped factors” model (with perfect labor markets) to analyze the impact of China’s integration on the growth rate of OECD countries, finding that it increases the profit from innovation, and hence, the long-run growth rate.

An example of a paper that quantifies the effects of a trade shock on labor markets is [Artuc, Chaudhuri, and McLaren \(2010\)](#), where the authors consider a dynamic model with labor mobility frictions across sectors. They estimate the variance of US workers' industry switching costs using gross flows across industries and simulate a trade liberalization shock. This and other papers in this literature, however, consider a small open economy set-up, disregarding general equilibrium effects across countries.⁵

Another strand of the literature quantifies models in which labor markets are imperfect taking into account general equilibrium effects across countries, but usually ignore multi-sector economies (and consequently that workers do not move freely between sectors) and are silent about transitional dynamics, due to the static nature of their framework. The most similar paper to mine in this area is [Heid and Larch \(2012\)](#), that considers search generated unemployment in an [Arkolakis, Costinot, and Rodriguez-Clare \(2012\)](#) environment and calculate international trade welfare effects in the absence of full employment.⁶

The validation of the predictions of my model also contributes to the literature that uses worker level information to identify effects of international trade on labor market outcomes, including out of employment dynamics. Examples are [Autor, Dorn, Hanson, and Song \(2014\)](#), which considers the China shock to identify impacts on labor markets in the US, and [Pfaffermayr, Egger, and Weber \(2007\)](#), which uses Austrian data to estimate how trade and outsourcing affect transition probabilities between sectors and/or out

⁵Another interesting paper is [Dix-Carneiro \(2014\)](#), which estimates a dynamic model using Brazilian micro-data to study the adjustment path after a Brazilian trade liberalization episode in the nineties. [Utar \(2011\)](#) calibrates a model using Brazilian data to answer a similar question, while [Helpman, Itskhoki, Muendler, and Redding \(2012\)](#) use linked employer-employee data to analyze also the trade effects in this same country, but with a greater focus on wage inequality. [Cosar, Guner, and Tybout \(2013\)](#) and [Utar \(2006\)](#) use Colombian firm level data to estimate a dynamic model of labor adjustment and study how the economy fairs following an import competition shock. [Kambourov \(2009\)](#) builds a dynamic general equilibrium sectoral model of a small open economy with sector-specific human capital, firing costs and tariff. He calibrates the model using Chilean and Mexican data to quantify the effects of trade reforms that took place in the seventies and in the eighties in Chile and in Mexico, respectively, finding that if a country does not liberalize its labor market at the outset of its trade reform, the reallocation of workers across sectors will be slower, reducing the gains from trade.

⁶[Felbermayr, Larch, and Lechthaler \(2013\)](#) construct a static one sector Armington model with frictions on the goods and labor markets and use a panel data of developed countries to verify the predictions of the model. [Felbermayr, Impullitti, and Prat \(2014\)](#) builds a dynamic two country one sector model a la [Melitz \(2003\)](#) to study inequality response to trade shocks in Germany, but consider only a static framework in their calibration exercise using matched employer-employee data from Germany.

of employment states.⁷

The paper is organised as follows. In Section 2 I present my model and discuss its most important implications. In section 3 I structurally estimate a sub-set of the parameters of the model, explain how to numerically compute my counterfactual exercise and present its results. In Section 4 I validate the key micro implications of the model using employer-employee panel data from the UK. I offer concluding comments in Section 5.

2 Model

My dynamic trade model incorporates frictional unemployment with endogenous job destruction (Pissarides, 2000) into a multi-country/multi-sector Costinot, Donaldson, and Komunjer (2012) framework. I also add labor mobility frictions between sectors using some features from Artuc, Chaudhuri, and McLaren (2010).

The model takes into account that labor markets are imperfect. The economy is composed of many countries and sectors. Workers without a job can choose the sector in which to search for employment according to their personal exogenous preferences. Within a sector, firms and workers have to engage in a costly and uncoordinated process to meet each other. Each sector produces many types of varieties, and consumers will shop around and pay the best available price for each type of variety (considering trade costs).

The model is tractable and allows the ability to quantify changes in real income per capita (my welfare proxy) following a trade shock (the emergence of China) considering not only the positive aspects associated with cheaper consumption goods but also the potential negative aspects associated with labor market adjustments. My dynamic framework will also enable me to study how different groups of workers are affected at different points in time. I start the section by providing the main components of the model. I then demonstrate how to compute the equilibrium and discuss some of the implications of the model.

⁷More broadly, the paper adds to a growing literature on the effects of trade shocks on labor markets, such as Revenga (1992), Bernard, Jensen, and Schott (2006), Filho and Muendler (2007), Dauth, Finden, and Suedekum (2012), Kovak (2013), Autor, Dorn, and Hanson (2013) and Costa, Garred, and Pessoa (2014), to cite just a few.

2.1 Set up

In terms of notation, $a_{k,i}^t$ represents variable ‘a’ in sector k in country i at time t . Some variables represent a bilateral relationship between two countries. In this case, the variable $a_{k,oi}^t$ is related to exporter o and importer i in sector k . Finally, in other cases it will be necessary to highlight that a variable depends on a worker, on a variety or on a different productivity level. In such cases, $a_{k,i}^t(l)$ means that the variable is related to the worker l , $a_{k,i}^t(j)$ is a variable associated with the variety j and $a_{k,i}^t(x)$ is linked to idiosyncratic productivity x . For the sake of simplicity, I omit the variety index j whenever possible.

2.1.1 Consumers

There are N countries. Each country has an exogenous labor force L_i and is formed by K sectors containing an (endogenous) mass of workers $L_{i,k}^t$ and an infinite mass of potential entrant firms. I assume that heterogeneous family members in each country pool their income, which is composed of unemployment benefits, labor income, firm profits and government lump-sum transfers/taxes, and maximize an inner C.E.S, outer Cobb-Douglas utility function subject to their income:⁸

$$\text{Max} \sum_t \sum_k \frac{\mu_{k,i}}{\varepsilon} \frac{\ln \int_0^1 (C_{k,i}^t(j))^\varepsilon dj}{(1+r)^t}.$$

Where k indexes sectors, $\varepsilon = (\sigma - 1)/\sigma$, σ is the constant elasticity of substitution (between varieties) and $C_{k,i}^t(j)$ represents consumption of variety j . $\mu_{k,i}$ is country i ’s share of expenditure on goods from sector k , and $\sum_k \mu_{i,k} = 1$. Note that consumers do not save in this economy. The dynamic effects in the model arise from labor market features, as shown below.

⁸Under the assumption of a “big household” with heterogeneous individuals (employed/unemployed in different sectors), and that households own some share of firms, household consumption equals its income $\text{Consumption}_i^t = \text{Income}_i^t = \text{Wages}_i^t + \text{Profits}_i^t + \text{UnempBenefits}_i^t + T\text{gov}_i^t$. The government uses lump-sum taxes/transfers $T\text{gov}_i^t$ to pay unemployment benefits and finance vacancy costs, as will see later. When the economy is aggregated, I must have that total expenditure in a country (consumption) will be equal to total revenue obtained with its sales around the world.

2.1.2 Labor Markets

Each sector has a continuum of varieties $j \in [0, 1]$. I treat a variety as an ex-ante different labor market. I omit the variety index j from this point forward, but the reader should keep in mind that the following expressions are country-sector-variety specific.

Firms and workers have to take part in a costly matching process to meet each other in a given market. This process is governed by a matching function $m(u_{k,i}^t, v_{k,i}^t)$. It denotes the number of successful matches that occur at a point in time when the unemployment rate is $u_{k,i}^t$ and the number of vacancies posted is $v_{k,i}^t$ (expressed as a fraction of the labor force). As in [Pissarides \(2000\)](#), I assume that the matching function is increasing in both arguments, concave and homogeneous of degree 1. Homogeneity implies that labor market outcomes are invariant to the size of the labor force in the market. For convenience, I work with $\theta_{k,i}^t = v_{k,i}^t / u_{k,i}^t$, a measure of labor market tightness.

So the probability that any vacancy is matched with an unemployed worker is given by

$$\frac{m(u_{k,i}^t, v_{k,i}^t)}{v_{k,i}^t} = q(\theta_{k,i}^t),$$

and the probability that an unemployed worker is matched with an open vacancy is

$$\frac{m(u_{k,i}^t, v_{k,i}^t)}{u_{k,i}^t} = \theta_{k,i}^t q(\theta_{k,i}^t).$$

Workers are free to move between markets to look for a job but not between sectors as will become clearer later. Unemployed workers receive a constant unemployment benefit b_i . New entrant firms are also free to choose a market in which to post a vacancy and are constrained to post a single vacancy. While the vacancy is open they have to pay a per period cost equals to κ times the productivity of the firm.

Jobs have productivity $z_{k,i}x$. x is a firm specific component, which changes over time according to idiosyncratic shocks that arrive to jobs with probability ρ , changing the productivity to a new value x' , independent of x and drawn from a distribution $G(x)$ with support $[0, 1]$. $z_{k,i}$ is a component common to all firms within a variety, constant over time and taken as given by the firm (I postpone its description until the end of this subsection). Conditional on producing variety j , each firm can choose its technology level and profit maximization trivially implies firms initially operate at the frontier, i.e., all vacancies are

opened with productivity z (at maximum x).

After firms and workers meet, production starts in the subsequent period. Firms are price takers and their revenue will be equal to $p_{k,i}^t z_{k,i} x$. During production periods, firms pay a wage $w_{k,i}^t(x)$ to employees.

When jobs face any type of shock (including the idiosyncratic one), firms have the option of destroying it or continuing production. Let $J_{k,i}^t(x)$ be the value of a filled vacancy for a firm. Then, production ceases when $J_{k,i}^t(x) < 0$ and continues otherwise. So, job destruction takes place when x falls below a reservation level $R_{k,i}^t$, where $J_{k,i}^t(R_{k,i}^t) = 0$. Defining the expected value of an open vacancy as $V_{k,i}^t$, I can write value functions that govern firms' behavior:

$$V_{k,i}^t = -\kappa p_{k,i}^t z_{k,i} + \frac{1}{1+r} [q(\theta_{k,i}^t) J_{k,i}^{t+1}(1) + (1 - q(\theta_{k,i}^t)) V_{k,i}^{t+1}]. \quad (1)$$

$$J_{k,i}^t(x) = p_{k,i}^t z_{k,i} x - w_{k,i}^t(x) + \frac{1}{1+r} [\rho \int_{R_{k,i}^{t+1}}^1 J_{k,i}^{t+1}(s) dG(s) + (1 - \rho) J_{k,i}^{t+1}(x)]. \quad (2)$$

The value of an open vacancy is equal to the per-period vacancy cost plus the future value of the vacancy. The latter term is equal to the probability that the vacancy is filled, $q(\theta_{k,i}^t)$, times the value of a filled vacancy next period, $J_{k,i}^{t+1}(1)$, plus the probability that the vacancy is not filled multiplied by the value of an open vacancy in the future, all discounted by $1 + r$.

I am implicitly assuming that firms are not credit constrained, even though some papers, e.g. (Manova, 2008), argue that financial frictions matter in international trade. So, governments will lend money to firms (financed by lump-sum taxes on consumers) as long as the value of posting a vacancy is greater or equal to zero. The value of a filled job is given by the per period revenue minus the wage cost plus the expected discounted value of the job in the future. The last term is equal to the probability that idiosyncratic shocks arrive multiplied by the expected value of the job next period, $\rho \int_{R_{k,i}^{t+1}}^1 J_{k,i}^{t+1}(s) dG(s)$, plus the value that the job would have in the absence of a shock times the probability of such event, $(1 - \rho) J_{k,i}^{t+1}(x)$.

$U_{k,i}^t$ and $W_{k,i}^t(x)$ are, respectively, the unemployment and the employment value for a worker. The value functions governing workers choices are:

$$U_{k,i}^t = b_i + \frac{1}{1+r} [\theta_{k,i}^t q(\theta_{k,i}^t) W_{k,i}^{t+1}(1) + (1 - \theta_{k,i}^t q(\theta_{k,i}^t)) U_{k,i}^{t+1}]. \quad (3)$$

$$W_{k,i}^t(x) = w_{k,i}^t(x) + \frac{1}{1+r} [\rho \left(\int_{R_{k,i}^{t+1}}^1 W_{k,i}^{t+1}(s) dG(s) + G(R_{k,i}^{t+1}) U_{k,i}^{t+1} \right) + (1 - \rho) W_{k,i}^{t+1}(x)]. \quad (4)$$

The unemployment value is equal to the per period unemployment benefit plus the discounted expected value of the job next period, given that workers get employed with probability $\theta_{k,i}^t q(\theta_{k,i}^t)$.

The value of a job for a worker is given by the per-period wage plus a continuation value, which is composed by two terms. First, the worker could get the value that the job would have in the absence of a shock, $W_{k,i}^{t+1}(x)$, a value that is realised with probability $1 - \rho$. If a shock arrives, with probability $\rho G(R_{k,i}^{t+1})$ the shock will be sufficiently bad to drive the worker into unemployment and he/she obtains only $U_{k,i}^{t+1}$ next period. If after the shock productivity remains above the destruction threshold, then the worker gets on average $\rho \int_{R_{k,i}^{t+1}}^1 W_{k,i}^{t+1}(s) dG(s)$.

Wages are determined by means of a Nash bargaining process, where employees have exogenous bargaining power $0 < \beta_{k,i} < 1$. Hence, the surplus that accrues to workers must be equal to a fraction $\beta_{k,i}$ of the total surplus,

$$W_{k,i}^t(x) - U_{k,i}^t = \beta_{k,i} (J_{k,i}^t(x) + W_{k,i}^t(x) - U_{k,i}^t - V_{k,i}^t). \quad (5)$$

2.1.3 Firm Entry and Worker Mobility within a Sector

Remember that workers and firms are free to look for jobs and to open vacancies across varieties. Hence, at every point in time the unemployment value must be equal for all varieties that are produced in equilibrium. Because markets are competitive, firms cannot obtain rents from opening vacancies. This implies that the value of a vacancy will be equal to zero in any market inside a country. These two conditions can be summarised as follows,

$$U_{k,i}^t(j) = U_{k,i}^t(j') \quad (6)$$

$$V_{k,i}^t(j) = V_{k,i}^t(j') = 0, \quad (7)$$

where here I explicitly indicate that the unemployment value and the value of an open vacancy are ex-ante market specific.

The fact that unemployment values are equalised across different varieties (condition 6) implies that $p_{k,i}^t z_{k,i}$ must be equal across markets that produce in equilibrium. Suppose that there are two varieties j and j' with distinct values of $p_{k,i}^t z_{k,i}$ and without loss of generality, assume that job market tightness is greater in market j , meaning that it is easier for a worker to find a job there. In this case, $p_{k,i}^t z_{k,i}$ must be greater in market j' , such that the lower probability of finding a job in this market is compensated by higher wages. However, if this is the case, firms will only be willing to open vacancies in market j , where they have a higher probability of finding a worker and can pay lower wages. Hence, the only possible equilibrium is a symmetric one where $\theta_{k,i}^t$ and $p_{k,i}^t z_{k,i}$ are equalised across varieties inside a sector in a country. Hence, all varieties also have the same labor market outcomes $R_{k,i}^t$ and $u_{k,i}^t$, as well as the same wage distribution. As will be discussed below, the only variety dependent variable is the price (a sketch of proof is presented in [Appendix A -](#)).

2.1.4 Worker Mobility between Sectors

Before looking for a job in a particular sector, an unemployed worker must choose a sector, and in contrast to the variety case, they do not move freely between sectors. I assume that each worker has a (unobserved by the econometrician) preference $v_k(l)$ for each sector, invariant over time. I further assume that workers know all the information necessary before taking their decision. Hence, the value of being unemployed in a particular sector for a worker l , $\hat{U}_{k,i}^t(l)$, is given by

$$\hat{U}_{k,i}^t(l) = U_{k,i}^t + v_k(l).$$

A high $v_k(l)$ relative to $v_{k'}(l)$ means that the worker has some advantage of looking for jobs in sector k relative to sector k' , for example, because he/she prefers to work in industry k as it is located in an area where he/she owns a property or his/her family members are settled. I do not provide a more detailed micro foundation for $v_k(l)$ to keep the model as simple as possible.

So the probability that a worker will end up looking for job in sector k while unemployed is given by

$$Pr(\hat{U}_{k,i}^t(l) \geq \hat{U}_{k',i}^t(l) \text{ for } k' = 1, \dots, K) = Pr(v_k(l) \geq v(l)_{k'} + U_{k',i}^t - U_{k,i}^t \text{ for } k' = 1, \dots, K). \quad (8)$$

For simplicity, I assume that $v_k(l)$ are i.i.d. across individuals and industries, following a type I extreme value (or Gumbel) distribution with parameters $(-\gamma\zeta, \zeta)$.⁹ The parameter ζ , which governs the variance of the shock, reflects how important non-pecuniary motives are to a worker's decision to switch sectors. When ζ is very large, pecuniary reasons play almost no role and workers will respond less to wage (or probability of finding a job) differences across sectors. In the polar case of ζ going to infinity, workers are fixed in a particular industry. When ζ is small the opposite is true and workers tend to move relatively more across sectors following unexpected changes in sectoral unemployment values.

This assumption implies a tractable way of adding labor mobility frictions to the model. In my counterfactual exercise, I will be able to analyze how different levels of mobility frictions influence the impacts on several outcomes following a trade shock. It also incorporates an interesting effect on the model: It allows sectors with high wages and high job-finding rates to coexist in equilibrium with sectors with low wages and low job-finding rates. If there were no frictions (workers were completely free to move) sectors with higher wages would necessarily have lower job-finding rates (as long as the value of posting vacancies were equal to zero in both sectors).

Note also from equation 5 that I am assuming that the bargaining game in one sector is not *directly* affected by the unemployment value in the other sectors. In my model, an employed individual (or an individual who has just found a job) behaves as if he/she is “locked-up” in the sector, i.e., his/her outside option at the bargaining stage in sector k is independent of the preference shocks $v_{k'}(l)$ in all other sectors. If I further assume that workers also benefit from this preference shock while they are employed, implying that a worker in sector k gets a total of $W_{k,i}^t(x) + v_k(l)$, then wages will not depend directly on the v 's. This assumption is similar to the one used in [Mitra and Ranjan \(2010\)](#).

⁹The Gumbel cumulative distribution with parameters $(-\gamma\zeta, \zeta)$ is given by $S(z) = e^{-e^{-(z-\gamma\zeta)/\zeta}}$ and I have that $E(z) = -\gamma\zeta + \gamma\zeta = 0$ and $Var(z) = \pi^2\zeta^2/6$, where $\pi \approx 3.1415$ and $\gamma \approx 0.5772$.

2.1.5 Job Creation and Job Destruction

Before workers decide on a sector to look for an open vacancy, job creation and job destruction take place in this economy:

$$u_{k,i}^{t+1} = u_{k,i}^t - m(u_{k,i}^t, v_{k,i}^t) + \rho G(R_{k,i}^t)(1 - u_{k,i}^t). \quad (9)$$

The unemployment rate in period $t + 1$ is equal to the rate at period t reduced by the number of new matches and inflated by the number of individuals who become unemployed (all terms expressed as a fraction of the labor force). One implicit assumption is that the labor force remains constant during this process, i.e., all movement of workers has already taken place. Notice also that this process takes place at the variety level, but the fact that the varieties are symmetric will permit me to easily aggregate it up to the sector level.

2.1.6 International Trade

All goods are tradable. Each variety j from sector k can be purchased at home at price $p_{k,i}^t(j)$ (which is equivalent to the term $p_{k,i}^t$ used in my description of the labor market, the only difference being that I now make explicit that it is a country-market specific variable), but local consumers can take advantage of the option provided by a foreign country and pay a better price. In short, consumers will pay for variety j the $\min\{d_{k,oi} p_{k,o}^t(j); o = 1, \dots, N\}$, where $d_{k,oi}$ is an iceberg transportation cost between exporter o and importer i , meaning that delivering a unit of the good requires producing $d_{k,oi} > 1$ units. I assume that $d_{k,ii} = 1$ and that it is always more expensive to triangulate products around the world than exporting goods bilaterally ($d_{k,oi}d_{k,ii'} > d_{k,oi'}$).

In any country i , the productivity component $z_{k,i}$ is drawn from a Frechet distribution $F_{k,i}(z) = e^{-(A_{k,i})^\lambda z^{-\lambda}}$, i.i.d for each variety in a sector. The parameter $A_{k,i} > 0$ is related to the location of the distribution: A bigger $A_{k,i}$ implies that a higher efficiency draw is more likely for any variety. It reflects home country's absolute advantage in the sector. $\lambda > 1$ pins down the amount of variation within the distribution and is related to comparative advantage: a lower λ implies more variability, i.e., comparative advantage will exert a stronger force in international trade.

As in [Eaton and Kortum \(2002\)](#), the fact that consumers shop for the best price around the world implies that each country i will spend a share $\pi_{k,oi}^t$ of its income on goods

from country o in sector k . It is not trivial to calculate this share, however. In the next subsection I will show that some equilibrium properties will deliver relatively simple expressions for it. For now, I just assume that it is possible to find an expression for these expenditure shares. In any case markets must clear

$$Y_{k,o}^t = \sum_{i'} \pi_{k,oi'}^t Y_{i'}^t, \quad (10)$$

where $Y_{i'}^t = \sum_k Y_{k,i'}^t$ is aggregate income in country i' . Following [Krause and Lubik \(2007\)](#) and [Trigari \(2006\)](#), I assume that the government pays for unemployment benefits and vacancy costs through lump sum taxes/transfers. This implies that aggregate income in a sector is given by the total revenue obtained from sales around the world.

2.2 Steady State

I analyze the steady state of the economy, henceforth omitting the superscript “t”. My first key equation is the Beveridge Curve, the point where transition from and to employment are equal. I find it by using Equation 9 and my definition of $\theta = v/u$,

$$u_{k,i} = \frac{\rho G(R_{k,i})(1 - u_{k,i})}{\theta q(\theta_{k,i})}. \quad (11)$$

From the free entry condition 7 combined with equation 1, I can find the value of the highest productivity job,

$$J_{k,i}(1) = \frac{(1+r)\kappa p_{k,i} z_{k,i}}{q(\theta_{k,i})}. \quad (12)$$

Equation 12 is the zero profit condition, which equates job rents to the expected cost of finding a worker. Using equation 2 to find $J_{k,i}(1)$ and $J_{k,i}(R_{k,i}) = 0$, and subtracting the second expression from the first, I obtain $J_{k,i}(1) = (1+r)p_{k,i} z_{k,i}(1 - \beta_{k,i})(1 - R_{k,i})/(r + \rho)$. By combining 12 with the last expression, I obtain:

$$\frac{\kappa}{q(\theta_{k,i})} = \frac{(1 - \beta_{k,i})(1 - R_{k,i})}{r + \rho}. \quad (13)$$

This is the job creation condition. It equates the expected gain from a job to its expected hiring cost. Note that this expression is independent of $z_{k,i}$ and $p_{k,i}$ because both revenue and costs for the firm are affected by these variables linearly.

I can find a relatively simple expression for wages that holds inside and *outside* the steady state. To do this, I combine equations 2, 3, 4, 5 and 13 to get:¹⁰

$$w_{k,i}(x) = (1 - \beta_{k,i})b_i + \beta_{k,i}p_{k,i}z_{k,i}(x + \kappa\theta_{k,i}). \quad (14)$$

Wages are increasing in prices and in the productivity parameters. And the job destruction condition can then be derived by manipulating expressions 2 and 14 (and using the fact that $J_{k,i}(R_{k,i}) = 0$):¹¹

$$\frac{b_i}{p_{k,i}z_{k,i}} + \frac{\beta_{k,i}\kappa\theta_{k,i}}{1 - \beta_{k,i}} = R_{k,i} + \frac{\rho}{r + \rho} \int_{R_{k,i}}^1 (s - R_{k,i}) dG(s). \quad (15)$$

It shows a positive relationship between $\theta_{k,i}$ and $R_{k,i}$: a greater number of vacancies (higher $\theta_{k,i}$) increases the workers' outside options, and hence, more marginal jobs are destroyed (higher $R_{k,i}$).

Symmetric varieties will permit me to find relatively simple expressions for the trade shares of each country around the world. Since the term $p_{k,i}z_{k,i}$ is constant across varieties and $z_{k,i}$ is a random variable, it must be that the price of each variety is also a random variable inversely proportional to $z_{k,i}$. There are some ways to see this. One of them is to use my wage equation 14 to find the highest wage in the sector, $w_{k,i}(1)$, and subtract from it the lowest wage, $w_{k,i}(R_{k,i})$. This will imply that:

$$p_{k,i}(j) = \frac{1}{z_{k,i}(j)} \frac{w_{k,i}(1) - w_{k,i}(R)}{\beta_{k,i}(1 - R_{k,i})} = \frac{\tilde{w}_{k,i}}{z_{k,i}(j)}. \quad (16)$$

$\tilde{w}_{k,i}$ is simply a way of writing the slope of the wage profile in the sector. For everything else constant, a steeper wage profile implies that the wage bill in the country is higher, and prices will also be higher.

I am now in the position to calculate trade shares around the world. Given iceberg trade costs, prices of goods shipped between an exporter o and an importer i are a draw from the random variable $P_{k,oi} = \frac{d_{k,oi}\tilde{w}_{k,o}}{Z_{k,o}}$. The probability that country o offers the cheap-

¹⁰First, I multiply equations 4 and 2 by $1 - \beta$ and β , respectively, and subtract the second from the first. Then, I use the sharing rule 5 to express $W_{k,i}^{t+1}(1) - U_{k,i}^{t+1}$ as a function of $J_{k,i}^{t+1}(1) = (1 + r)\kappa p_{k,i}'z_{k,i}/q(\theta_{k,i}')$ (see 13 above), and substitute for $W_{k,i}^{t+1}(1) - U_{k,i}^{t+1}$ in equation 3. By combining the two expressions obtained, I get the wage equation 14.

¹¹I substitute for $w_{k,i}(x)$ in 2 using expression 14 to find the value of $J_{k,i}(x)$. Then, I substitute for $J_{k,i}(x)$ inside the integral of equation 2 and evaluate the expression obtained at $x = R_{k,i}$.

est price in country i is

$$H_{k,oi}(p) = Pr(P_{k,oi} \leq p) = 1 - F_{k,o}(d_{k,oi}\tilde{w}_{k,o}/p) = 1 - e^{-(pA_{k,o}/d_{k,oi}\tilde{w}_{k,o})^\lambda}, \quad (17)$$

and since consumers will pay the minimum price around the world, I have that the distribution of prices actually paid by country i is

$$H_{k,i}(p) = 1 - \prod_{o'=1}^N (1 - H_{k,o'i}(p)) = 1 - e^{-\Phi_{k,i}p^\lambda}, \quad (18)$$

where $\Phi_{k,i} = \sum_{o'} (A_{k,o'}/d_{k,o'i}\tilde{w}_{k,o'})^\lambda$, is the parameter that guides how labor market variables, technologies and trade costs around the world govern prices. Each country takes advantage of international technologies, discounted by trade costs and the wage profile of each country.

Hence, I can calculate any moment of the price distribution, including the exact price index for tradable goods in steady state,

$$P_i = \prod_k (P_{k,i})^{\mu_{k,i}}, \quad (19)$$

where $P_{k,i} = \gamma(\Phi_{k,i})^{(-1/\lambda)}$, $\gamma = [\Gamma(\frac{\lambda+1-\sigma}{\lambda})]^{1/(1-\sigma)}$ and Γ is the Gamma function (and remember that $\mu_{k,i}$ is the share of country i 's income allocated to consumption of sector k goods).

As in [Eaton and Kortum \(2002\)](#), I calculate the probability that a country o provides a good at the lowest price in country i in a given sector:

$$\pi_{k,oi} = \frac{(A_{k,o}/d_{k,oi}\tilde{w}_{k,o})^\lambda}{\Phi_{k,i}}. \quad (20)$$

$\pi_{k,oi}$ decreases with labor costs of exporter o (or with trade costs $d_{k,oi}$), and increases with absolute advantage of exporter o . Notice that expression 16 also holds outside the steady state, and hence, trade shares at any time t can be calculated in a similar fashion.

Eaton and Kortum also show that the price per variety, conditional on the variety being supplied to the country, does not depend on the origin, i.e., the price of a good that i actually buys from any exporter o also has the distribution $H_{k,i}(p)$. This implies that average expenditure does not vary by country of origin. Exporters with cheaper wages or

with lower trade costs take advantage by exporting a wider range of goods. Because there is a continuum of goods, it must be that the expenditure share of country i on varieties coming from o is given by the probability that o supplies a variety to i ,

$$\frac{X_{k,oi}}{X_{k,i}} = \pi_{k,oi}, \quad (21)$$

where $X_{k,oi}$ is country i 's expenditure on goods from o , and $X_{k,i} = \sum_{o'} X_{k,o'i}$ is its total expenditure in a given sector.

To close the model I have to find an expression for income in country i . Income in the sector is given by its total revenue¹²

$$Y_{k,o} = \tilde{w}_{k,o} L_{k,o} (1 - u_{k,o}) (G(R_{k,o}) + \int_{R_{k,o}}^1 s dG(s)). \quad (22)$$

The market clearing condition in steady state implies that

$$Y_{k,o} = \sum_{i'} X_{k,oi'} = \sum_{i'} \pi_{k,oi'} \mu_{k,i'} Y_{i'}. \quad (23)$$

Finally, the Gumbel distribution allows me to calculate a simple expression for the number of individuals attached to each sector by using expression 8. I must have that the share of workers in each sector equals the probability that a worker is looking for a job in that sector whenever he/she is unemployed. And it can be shown that this probability will be equal to:¹³

$$\frac{L_{o,k}}{\sum_{k'} L_{o,k}} = \frac{e^{U_{k,i}/\zeta}}{\sum_{k'} e^{U_{k',i}/\zeta}}, \quad (24)$$

where $U_{k,i} = \frac{1+r}{r} (b_i + \frac{\beta_{k,i}}{(1-\beta_{k,i})} \kappa p_{k,i} z_{k,i} \theta)$.

¹²To calculate production I follow [Ranjan \(2012\)](#). First, note that output changes over time equals (i) the output from new jobs created at maximum productivity $\theta_{k,i} q(\theta_{k,i}) u_{k,i}$, plus (ii) the output of the existing jobs that are hit by a shock and survive $\rho \int_{R_{k,i}}^1 s dG(s)$, minus (iii) the loss in production due to destroyed jobs $\rho Q_{k,i}$, where $Q_{k,i}$ equals production per worker in the sector. Setting the total change to zero, I find $Q_{k,i} = (1 - u_{k,i}) (G(R_{k,i}) + \int_{R_{k,i}}^1 s dG(s))$. I then multiply it by $\tilde{w}_{k,i}$ and by the total number of workers in each variety market and integrate over the mass of varieties being produced to find revenue. The only non-constant term among varieties is the number of workers, that must sum up to $L_{k,i}$. I also use the fact that in Pissarides' model rescaling the labor force does not affect equilibrium outcomes.

¹³See [Artuc, Chaudhuri, and McLaren \(2010\)](#), online Appendix, for a similar proof.

To find my steady state equilibrium, note that from the labor market equations (11, 13 and 15) I can find the values of $R_{i,k}$, $\theta_{i,k}$ and $u_{i,k}$ as a function of $\tilde{w}_{i,k}$ for every country and sector. I can then use the trade share equation, also expressed as a function of $\tilde{w}_{i,k}$, together with my market clearing condition above to find the relative values of the slope of the wage profile that balance trade around the world. Finally, the labor force size in each of the sectors can be determined through the equation that determines the share of unemployed individuals in each sector. Naturally, all these effects take place simultaneously, and hence, I have to solve the system of non-linear equations described above to find my endogenous variables.

In short, I use the Beveridge curve (11), the job creation (13) and job destruction (15) conditions, the market clearing equation (23) together with the trade share expressions (20) and the unemployment share condition (24), to find my endogenous variables $R_{i,k}$, $\theta_{i,k}$, $u_{i,k}$, $\tilde{w}_{i,k}$, $L_{i,k}$ for all i 's and k 's. There are a total of $N \times K$ equations of the type of Equation 23, but only $N \times K - 1$ independent ones. I have to assume that the sum of all countries' income is equal to a constant.

2.3 Implications of the Model

Consider a rise in productivity ($A_{k,o}$) in a foreign country o or a fall in trade costs ($d_{k,oi}$) from the same foreign country to home country i , holding productivity in the home country fixed. Consumers in the home country will benefit as they have access to cheaper goods coming from abroad (see equation 19). However, this can also have negative effects in the labor market. If the demand for goods produced locally fall, prices of local goods will fall, implying that jobs will have to be destroyed in the home country¹⁴ and nominal wages will decrease. Note that the jobs destroyed in any country-sector following a bad shock are the ones with low idiosyncratic productivity x . These are the low-paid (low-productivity) jobs in the sector that become non-profitable after a fall in prices.

The effect on real wages is ambiguous, however. For example, if the rise in productivity takes place in a sector k in which the home country has a high level of production and most part of it is exported (meaning that the consumption share $\mu_{k,i}$ is low in the

¹⁴Note that the assumption that the unemployment benefit b is constant plays an important role in my model. It will imply that wages will *not* absorb all the impact from shifts in productivity/prices in the new equilibrium and, consequently, such shocks will have an effect on the unemployment rate even in the long-run.

home country), real wages will tend to fall at home in sector k , as the benefits from cheaper prices are small (if $\mu_{k,i}$ is zero there is no benefit at all) and nominal wages decrease in this sector as the foreign country increases its market share around the world. On the other hand, if home country i has a low production level in sector k but has a high consumption share in this sector (high $\mu_{k,i}$), then real wages will most likely rise as the fall in prices will tend to be the dominant effect in the home country.

Workers have preferences over sectors in my model. This means that after a trade shock some (but not all) unemployed workers will be willing to move from sectors that experience losses and to start looking for jobs in other sectors. Which sectors lose or gain in each country will depend on the new configuration of comparative and absolute advantages around the world following the trade/productivity shock.

The model also delivers interesting dynamic implications that are deeper investigated in my numerical exercise performed in the next section. After analyzing the results obtained with my counterfactuals, I test some of the observed partial-equilibrium implications of the model in Section 4 by drawing on detailed worker-level micro-data from one open developed economy, the UK.

3 Quantification of the Model

My model provides a rich set of mechanisms that are difficult to study analytically. In this section, I perform a counterfactual numerical exercise to analyze how advanced economies responded to the emergence of China in a world with imperfect labor markets. This will allow me to analyze both the transition path to a new equilibrium and the heterogeneous effects across sectors within countries. My calculations take into account not only that labor markets are imperfect and that workers do not move freely across sectors, but also that exporting sectors can gain from more trade with China and that consumers have access to cheaper imported goods.

In the first part of this section, I estimate three parameters that will be used in my counterfactual. In the second part, I demonstrate how to obtain the remaining parameters (either by calibration from data or from previous papers) and the methodology used to construct my numerical exercise. In the last part, I present the results and conduct a few robustness tests considering different parameter values.

3.1 Structural Estimation

I start by estimating a sub-set of the parameters for the UK (ζ and ρ). Then, I proceed to estimate the trade elasticity (λ) using bilateral trade flows. The labor share (β), the expenditure share (μ) and the productivity parameter that drives absolute advantage (A) will be taken directly from the data. All the other parameters will either be calibrated or taken from previous papers.

3.1.1 Labor Market Parameters

I estimate the probability of an idiosyncratic shock arriving to a job (ρ) and the parameter that governs labor mobility frictions across sectors (ζ).

These labor market parameters are estimated only for the UK and used for all other countries in my counterfactuals. Naturally, it would be more accurate to estimate the parameters for all the countries considered in the next sub-section, and I recognize that this approximation may be unsuitable especially for economies that are very distinct, but data restrictions do not allow me to follow this route and I believe that applying UK parameters to other countries can still provide important qualitative insights for adjustment dynamics. Estimating these parameters for other countries is an important topic for future work but is beyond the scope of this paper.

The data used to estimate labor market variables are from different sources and the regressions used to obtain ρ and ζ are at the industry level (ISIC3 2-digit), at yearly frequency from 2002 to 2007. Total employment, job creation, and job destruction by industry are from the Business Structure Database (BSD). Unemployment by sector is obtained from the Labor Force Survey (LFS) micro-data. I assume that unemployed individuals are attached to the last industry they worked for, and this information is available in the LFS.¹⁵ Wage data are from the Annual Survey of Hours and Earnings (ASHE) and vacancy data are from the NOMIS, provided by the UK Office for National Statistics.

I calculate β_k 's as the share of labor costs in value added in each sector in the UK. They are obtained from firm-level micro-data, the Annual Respondent Database (ARD), which I aggregate up to the 2-digit ISIC3 level. I set the interest rate $r = 0.031$ —a value

¹⁵Not all unemployed in the LFS respond to the question related to the last industry of work, so I assume that the industry share of unemployed individuals is equal to the industry share of unemployed that actually responded to this question, something that is likely to add measurement error to my estimates.

in the range used by Artuc, Chaudhuri, and McLaren (2010) that corresponds to a time discount factor of approximately 0.97.

I estimate ρ by using the fact that the total number of jobs destroyed in a sector at any point in time is $\rho G(R_k^t)(1 - u_k^t)L_k^t$. My empirical job destruction measure is calculated using the BSD. It is the sum of all jobs lost in an industry either because firms decreased size or ceased to produce in a particular year. I then run the following industry-level regression,

$$\ln(\text{JobDestruction}_k^t) = \ln(\rho) + \ln((1 - u_k^t)L_k^t) + \ln(G(R_k^t)) + \varepsilon_k^t, \quad (25)$$

where ε_k^t is a measurement error. Since I do not observe $G()$, I control for a polynomial function (of 4th degree) of R_k^t (the idiosyncratic productivity threshold below which jobs are destroyed) in the sector.¹⁶ The first column of Table 1 shows my OLS result. The second column restricts the coefficient of $\ln((1 - u_k^t)L_k^t)$ to be equal to one, while column 3 additionally includes instruments suggested by the model: the lagged right-hand side variables. Observe that the value of ρ decreases in the 2SLS estimates. The value I use in my counterfactuals (column 3) corresponds to approximately $\rho = 0.0129$.

Table 1: Estimates of ρ

	(1)	(2)	(3)
	OLS	OLS	2SLS
Total Job Destruction			
$\ln(\rho)$	-2.697** (1.228)	-2.901** (1.163)	-4.342* (2.421)
Restricted Coefficients	-	Yes	Yes
Obs	282	282	282

NOTES: $\ln(\rho)$ is the constant term in equation 25, which has total job destruction as a dependent variable and a 4th degree polynomial function of R_k^t and the logarithm of the total number of employed individuals ($\ln((1 - u_k^t)L_k^t)$) as controls. Yearly data (from 2002 to 2007) at the industry-level (ISIC3 2-digit) obtained from ARD, BSD, NOMIS and LFS. Column (3) uses the lagged control variables as instrument. Clustered standard errors at the industry-level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ζ can be found using the shares of workers employed in each sector. My model predicts that the number of workers increase in a sector whenever wages increase and/or it is easier to find a job. So, I use an equation that relates increases in the number of employed individuals to changes in wages and job-finding rates in a sector. To obtain

¹⁶I obtain R_k^t using ARD. First, I calculate average labor productivity by firm. To adjust for outliers I windsorize the labor productivity measure per industry, both at the top 99th percentile and at the bottom 1st percentile. Second, I divide each firm-level labor productivity by the maximum value in the industry, such that the distribution of productivity in each sector is between zero and one as suggested by the model. Third, I obtain R_k^t as the minimum of the normalised labor productivity measure in each sector.

this equation, I make the strong assumption that the economy is in a different steady state in every year of my sample.

From the steady state versions of equations 3 and 4, I can write the following expression:¹⁷

$$\Delta \ln(L_k) = \frac{1}{\zeta} \Delta \frac{JFR_k w_k(1)}{1+r} + \psi_k + \psi_t + \hat{\varepsilon}_k^t, \quad (26)$$

where JFR_k^t (equivalent to $\theta_k^t q(\theta_k^t)$ in my model) is the probability of a worker finding a job in the sector, and $\hat{\varepsilon}_k^t$ is a measurement error. This is obtained directly as total job creation (from BSD) divided by the total number of unemployed (calculated using LFS and BSD). $w_k^t(1)$ represents the maximum wage in the sector. To account for possible outliers in the data, I use the 95th percentile of the wages in the industry from ASHE instead of the maximum value. The estimates consider normalised wage values such that the average in the sample is equal to 1. Results are shown in Table 2.

Table 2: Estimates of ζ

	(1) OLS	(2) 2SLS
Change in the Labor Force		
$1/\zeta$	0.032*** (0.008)	0.027 (0.029)
95 th Percentile	Yes	Yes
Obs	285	285

NOTES: ζ is the coefficient of $\Delta \frac{JFR_k w_k(1)}{1+r}$ in equation 26, which uses the change in the number of workers in an industry over time as a dependent variable and fixed effects for time and industry as controls. $\Delta \frac{JFR_k w_k(1)}{1+r}$ is the difference over time between the product of the job finding rate and maximum wages (calculated as the 95th percentile) in the sector. Yearly data (from 2002 to 2007) at the industry-level (ISIC3 2-digit) obtained from ASHE, BSD, NOMIS and LFS. Column (2) has the lag of $\frac{JFR_k w_k(1)}{1+r}$ as instrument. Estimates consider normalised wage values such that the average in the sample is equal to 1. Clustered standard errors at the industry-level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 1 shows my OLS estimates, while the second column presents the 2SLS estimates using the lagged value $JFR_k w_k(1)$ as an instrument. My estimates of ζ are higher than the ones in Artuc, Chaudhuri, and McLaren (2010), corresponding to $\zeta = 36.57$ on column 2, the value that will be used in my counterfactuals. Indeed, in my

¹⁷First, from 3 and 4 I can write $U_k^{tss1} - U_k^{tss0} = \frac{JFR_k^{tss1} w_k^{tss1}(1)}{1+r} - \frac{JFR_k^{tss0} w_k^{tss0}(1)}{1+r} + \Theta(k, t)$, where JFR_k^t is the job finding rate (equivalent to $\theta_k^t q(\theta_k^t)$ in my model) and $w_k^t(1)$ is the maximum wage in the sector. $t = tss0$ and $t = tss1$ represent the final and initial steady state, respectively. $\Theta(k, t)$ is a sector-time-level function that depends on present and future variables in the sector, which I approximate using two distinct fixed effects, one for time and the other for sectors. Obviously this is not a very rich approximation, but permits me to take a very simple equation to the data, which is obtained by taking logs and first differences of 24 and using the value of $U_k^{tss1} - U_k^{tss0}$ written above.

model this coefficient should be higher as it captures all the labor movement frictions between sectors, while in their paper part of the rigidity is also captured by high fixed moving costs.¹⁸ So, using their estimates in my model would imply that workers are much more mobile than they actually are, possibly leading my real income per capita calculations to overestimate gains (or underestimate losses).

3.1.2 Matching Function, Idiosyncratic Productivity and Vacancy Costs

I assume the following constant returns to scale matching function:

$$m(v_k^t, u_k^t) = m(u_k^t)^{1-\delta} (v_k^t)^\delta.$$

I use the estimates from [Borowczyk-Martins, Jolivet, and Postel-Vinay \(2013, Table 1\)](#), $\delta = 0.412$. To find m , I start with an estimate of 0.231 (from the same paper) and adjust the parameter such that the probabilities of finding workers and vacancies are always between 0 and 1. The value that will be used is $m = 0.19$.

In all my counterfactuals I assume that idiosyncratic productivity shocks are uniformly distributed between zero and one ([Ranjan, 2012](#)). This assumption was not used in my previous estimates. To verify the robustness of my counterfactuals to this and other assumptions I perform additional counterfactual exercises with alternative parameter values.

The parameter κ , the cost of posting vacancies, is also obtained from another paper. I consider the same value used in [Shimer \(2005\)](#): 0.213.

3.1.3 Trade Parameters

The trade elasticity λ is estimated using a gravity equation. First, I obtain bilateral trade flows from the World Input Output Database (WIOD).¹⁹ Information on labor market characteristics by sector and country comes from the EU KLEMS dataset.²⁰ As in [Costinot, Donaldson, and Komunjer \(2012\)](#), I measure the variation in productivity

¹⁸Another reason is that in my model this is the elasticity of employed and unemployed workers in the UK, while in their model they consider only employed individuals in the US. Hence, workers in their model take into account only wages when moving across sectors, while here workers also look at the probability of finding a job. Secondly, they consider average wages, while I consider the maximum wage (95th percentile) as suggested by my model.

¹⁹See [Stehrer, de Vries, Los, Dietzenbacher, and Timmer \(2014\)](#) for more details on this database.

²⁰See [O'Mahony and Timmer \(2009\)](#) for details on the methodology used to construct the dataset.

across countries and industries using differences in producer price indexes. Producer price data is taken from the GGDC Productivity Level Database, which is calculated from raw price data observations at the plant level for several thousand products (often with hundreds of products per industry, which can be associated with varieties in my model, as in Costinot, Donaldson, and Komunjer, 2012).²¹ These prices are aggregated into a producer price index at the industry level using output data. I use the inverse of this measure as my A_k^t to identify the trade elasticity.

All my gravity estimations are based on the year 2005, and 1997 lags are used as instruments for my productivity parameter A_k^t (GGDC data is available only for these two years). To compare my estimates to Costinot, Donaldson, and Komunjer (2012), I restrict my sample to the same 21 developed countries they consider plus China, and I exclude the so called non-tradable sectors (services). I add China as an importer in all regressions and whenever possible as an exporter since GGDC (1997) and KLEMS data are not available for this country.

By taking logs of expression 20, I obtain the following gravity equation: $\ln(X_{oi}^k) = \lambda \ln(A_o^k) + \ln(X_i^k / \Phi_{k,i}) - \lambda \ln(\tilde{w}_o^k) + \lambda \ln(d_{k,oi})$.

Following Head and Mayer (2013), I replace $\ln(X_i^k / \Phi_{k,i})$ with an importer-product fixed effect. I do not observe \tilde{w}_o^k .²² In order to control for the last two terms of the gravity equation and still be able to identify λ as the coefficient of A_k^t , I replace their values by a sector fixed effect, an exporter fixed effect, an importer-exporter fixed effect and a 4th degree polynomial function of labor compensation, total employment, hourly wage and labor share for each exporter-sector pair.²³ So, I run the following regression at the sector-exporter-importer-level

$$\ln(X_{oi}^k) = \lambda \ln(A_o^k) + \bar{f}_{k,o} + \chi_{ik} + \chi_k + \chi_o + \chi_{oi} + \bar{\epsilon}_{oi,k}, \quad (27)$$

where the χ are the respective fixed effects and $\bar{f}_{k,o}$ is the 4th degree polynomial of exporter labor market variables. $\bar{\epsilon}_{oi,k}$ is a measurement error. The results are shown in Table 3:

Controlling for labor market characteristics decreases the coefficient, while using

²¹See Inklaar and Timmer (2008) for more details.

²²With the data used in the paper, \tilde{w}_o^k could be recovered only for the UK.

²³Including measures for trade costs such as distance, RTA's and common language do not change the coefficient values significantly, and it is difficult to interpret their coefficients as they are obtained only after some fixed effects are dropped. Hence, I choose to omit them.

Table 3: Estimates of λ

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	2SLS
Bilateral Trade Flows				
λ	1.120*** (0.458)	1.791*** (0.471)	1.178*** (0.331)	4.934*** (1.327)
China as an Exporter	Yes	-	-	-
Labor Market Controls	-	-	Yes	Yes
Obs	6866	6194	6194	6194

NOTES: λ is the coefficient of the productivity measure A_o^k in equation 27, which uses bilateral trade flows at the sector level as the dependent variable and fixed effects for industry, importer-sector and exporter fixed effects. Labor Market Controls is a 4th degree polynomial function of labor compensation, total employment, hourly wage and labor share for each exporter-sector pair. Data is a cross-section of bilateral trade data in 2005 at the WIOD industry-level (roughly ISIC3 2-digit). Data obtained from WIOD, KLEMS and GGDC. Column (4) has the lag of A_o^k (1997 value) as instrument. Clustered standard errors at the exporter-industry level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

lagged productivity values as instruments increases it considerably. I use the value of 4.934 in my counterfactuals, which is not far from Costinot, Donaldson, and Komunjer (2012) estimates.

3.2 Counterfactuals

The counterfactuals performed are meant to understand how the rise of China affected other countries in the world, especially the UK. The trade shock I have in mind is one whereby Chinese productivity increases ($A_{k,CHN}$ rises 25%) and all trade costs between China and the rest of the world fall ($d_{k,oCHN}$ and $d_{k,CHNi}$ fall 25%) in all sectors apart from services. This shock implies that China's export shares around the world increases from 0.12 to 0.2 between the two steady states. This corresponds to a growth of 64% in China's share of world exports, a magnitude not very different from the one observed between 2000 (the year before China joined the WTO) and 2004 in the WIOD data (65%). So, my shock aims to mimic the four year period following China's entry into the WTO in terms of percentage change in the its export share. I study how countries respond to this shock during the transition to a new steady state.

To calculate the initial equilibrium, I use the parameters estimated in the previous subsection. My counterfactuals also require values for worker's labor share ($\beta_{k,i}$) and the size of the labor force in each country, both obtained from the WIOD - Socio Economic Accounts.²⁴ Labor shares are calculated as labor compensation divided by value added

²⁴ Available at http://www.wiod.org/new_site/database/seas.htm.

(at the same level as the WIOD bilateral trade data, roughly the ISIC3 2-digit industry).²⁵ The expenditure share of each country on goods from a particular sector ($\mu_{k,i}$) is calculated from the WIOD data. The values of $\beta_{k,i}$'s and $\mu_{k,i}$'s can be seen in the Appendix, Table B.1.

In my counterfactual exercise, I reduce the number of countries to six due to computational reasons. The “countries” chosen are China, US, UK, European Union (EU), the Rest of the World (RoW) Developed and the RoW Developing. The last economies are an aggregation of the remaining WIOD countries, which were separated in high-income (Australia, Japan, Canada, South Korea and Taiwan) and low-income countries (Brazil, India, Indonesia, Mexico, Turkey and Russia). I also aggregate the economy into five sectors:

-*Energy and Others*: Energy, Mining and quarrying; Agriculture, Forestry and fishing;

-*Low-Tech Manufacturing*: Wood products; Paper, printing and publishing; Coke and refined petroleum; Basic and fabricated metals; Other manufacturing.

-*Mid-Tech Manufacturing*: Food, beverage and tobacco; Textiles; Leather and footwear; Rubber and plastics; Non-metallic mineral products.

-*High-Tech Manufacturing*: Chemical products; Machinery; Electrical and optical equipment; Transport equipment.

-*Services*: Utilities; Construction; Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel; Wholesale trade; Retail trade; Hotels and restaurants; Land transport; Water transport; Air transport; Other transport services; Post and telecommunications; Financial, real estate and business services; Government, education, health and other services; Households with employed persons.

The manufacturing rank of technology is based on R&D intensity in the US in 2005 from OECD STAN database. The productivity measures ($A_{k,i}$'s) are from the GGDC database (described above). I aggregate countries and sectors using value added as weights. The productivity parameters used in the counterfactuals are displayed in Table B.2, which indicates that China has an absolute advantage in all the sectors. This advantage is most likely because GGDC is based on price data, and China provides the

²⁵I intentionally decrease China's share of value added in agriculture to the second-highest value in agriculture, which in this world is 0.32. The original value corresponded to an extremely high value of 0.8 and was generating problems in my numerical simulations.

cheapest goods globally. This measure does not take into account, for example, that the UK produces higher quality goods such as airplanes and more advanced cars. Thus, instead of estimating trade costs, I calibrate an additional parameter that *includes* trade costs such that trade shares ($\pi_{k,oi}$) are as close as possible to the values observed in the WIOD. Put another way, I substitute for $d_{k,oi}$ (the iceberg trade cost described previously) in all my expressions using $\bar{d}_{k,oi} = d_{k,oi} * \omega_{k,oi}$, where $\omega_{k,oi}$ is an unobserved component that accounts, for example, for quality difference across countries. Then, I calibrate the $\bar{d}_{k,oi}$'s such that trade shares are as close as possible to the ones observed in the data. The fact that trade costs are not identified does not play a large role in my counterfactuals, since I am interested in their relative changes (and also in relative income changes).²⁶

In my initial steady state equilibrium, I set the unemployment benefit (b_i) to a fraction of the average wage in each country: UK 0.36, China 0.18, US 0.4, EU 0.5, RoW Developed 0.5 and RoW Developing 0.14.²⁷ These values will be fixed throughout my counterfactual exercises, as described in the model. This assumption is not innocuous. It will imply that wages will *not* absorb all the impact from shifts in productivity/prices, and consequently, such shocks will have an effect on the unemployment rate.

My parameter ζ is held as 36.57 times the average wage in each country in the initial equilibrium, and then kept fixed as well.²⁸ The summary of all the parameters used are in Table 4.

I am then able to find the values of $R_{k,i}$, $u_{k,i}$, $\theta_{k,i}$, $\tilde{w}_{k,i}$ and $L_{k,i}$ in my initial steady state. The model performs relatively well in terms of fitting the size of the labor force in each sector.²⁹

²⁶I also assume that $\bar{d}_{k,oo} = 1$ for all countries, as I am able to calibrate only relative values for \bar{d} 's. One consequence of calibrating trade costs this way is that China and the RoW developing will have access to the cheapest goods in the world because they are produced by these two countries and their exporting costs are relatively high. This implies that in my initial equilibrium, the rich countries (the UK, US and Eurozone) have a high expenditure on goods around the world but not necessarily the highest real income.

²⁷These values are based on [Munzi and Salomaki \(1999\)](#) and [Vodopivec and Tong \(2008\)](#), for the UK, EU, RoW Developed and China. The UK value is relatively low because much of the retained income after a job loss in the UK does *not* come from unemployment benefits, as this is quite small (Job Seekers' Allowance (JSA) nowadays in the UK varies between £57.35 and £113.70 per week and covers a period of approximately 6 months). The US value is based on [Shimer \(2005\)](#), and the value of RoW developing was set slightly below that of China. In my initial steady, state unemployment rates are 0.0479, 0.0575, 0.0256, 0.0399, 0.0391 and 0.0235 in the UK, EU, China, US, RoW Developed and RoW developing, respectively.

²⁸This implies that different countries will have different values for this parameters, but all the countries will have the same labor market frictions as the variance of the unobserved preference over sectors will be the same in each country.

²⁹The labor force predicted by the model and the labor force observed in the data have a correlation of 63%.

Table 4: Parameters used in the Counterfactuals

Parameter	Description	Value	How was the Parameter Obtained	Country-Specific	Sector-Specific
ρ	Constant Rate of Job Destruction	0.013	Estimated for the UK and Replicated to other Countries (Table 1)	No	No
κ	Cost of Posting Vacancies	0.213	Based on Shimer (2005)	No	No
ζ	Labor Mobility Friction Between Sectors	See Notes Below	Estimated for the UK and Replicated to other Countries (Table 2)	Yes	No
δ	Matching Function Elasticity	0.412	Based on Borowczyk-Martins, Jolivet, and Postel-Vinay (2013)	No	No
m	Matching Function Efficiency	0.190	Based on Borowczyk-Martins, Jolivet, and Postel-Vinay (2013)	No	No
b	Unemployment Benefits	See Notes Below	Based on Munzi and Salomaki (1999) and Vodopivec and Tong (2008)	Yes	No
λ	Trade Elasticity	4.934	Estimated using bilateral trade flows (Table 3)	No	No
d	Trade Costs	See Notes Below	Calibrated to Match Trade Flows from WIOD data in 2005	Yes	Yes
A	Countries' Absolute Advantage	See Table B.2	GGDC Dataset	Yes	Yes
β	Labor Share of the Surplus of the Match	See Table B.1	WIOD - Socio Economic Accounts Dataset	Yes	Yes
μ	Expenditure Share on a Sector	See Table B.1	WIOD Dataset	Yes	Yes
r	Annual Interest Rate	0.031	Based on Artuc, Chaudhuri, and McLaren (2010)	No	No

NOTES: Parameter values used in the main counterfactual. 1 additionally use unemployment benefits, expressed as a fraction of average wages in each country in the initial equilibrium: UK 0.36, China 0.18, US 0.4, EU 0.5. RoW Developed 0.5 and RoW Developing 0.14. $\zeta = 36.57$ is also expressed as the multiple of average wages in each country in the initial equilibrium. Trade costs and other unobserved components that drive trade (such as unobserved quality of products) are calibrated such that trade flows match WIOD data in 2005, but the two terms cannot be separately observed. See also Tables B.1 and B.2 for productivity components and labor and expenditure shares used in the counterfactuals.

Details about the method used to compute the transition path can be found in the Appendix (Subsection B.2). The objective is to find a rational expectations path between the initial and the final steady state. I use a type of multiple shooting algorithm that builds on Artuc, Chaudhuri, and McLaren (2010), Artuc, Chaudhuri, and McLaren (2008) and Lipton, Poterba, Sachs, and Summers (1982). In my algorithm I have to assume a certain number of years for the transition period to occur.³⁰ I consider 25 years in my numerical exercises, but the higher the number of years assumed the closer the variables of the system are to their new steady state values in the final period of the algorithm. In my numerical simulations approximately 90% of the real income adjustment has taken place in year 25.

3.2.1 Results

Real income (or real consumption) is defined as income divided by the price index: Y_i/P_i . The analysis will be relative to the initial equilibrium values. Following several papers in the international trade literature, I use real income per capita as a proxy for welfare (in Appendix B.4 I present a measure that incorporates changes in workers' utility from switching sectors, as well as changes in their real value functions).

Figure 1a shows the evolution of countries' real income per capita (or real consumption per capita) over the 25 years following the fall in trade costs and productivity gains in China. One can see that income instantly increases in all countries, either because the countries are able to export more to China or because consumers have access to cheaper goods.³¹ All countries benefit in the new steady state as well. Chinese citizens experience large income gains of more than 23% during the transition period (see Figure 1b).

Some countries, such as the EU, experience an initial overshooting in real income (initial gains of approximately 1.1%). One reason behind this is that after the shock wages (and prices) do the majority of the “heavy-lifting” in the short-run to keep markets cleared, as production is rigid (especially upwards) because it takes time for jobs to be created due to the search and matching frictions in the labor market. Immediately after the shock, nominal wages rise in the exporting sectors and fall in the ones facing

³⁰Such types of non-linear systems of equations can only be guaranteed to converge asymptotically - see Lipton, Poterba, Sachs, and Summers (1982).

³¹Itskhoki and Helpman (2014) carefully characterize the transition period following a trade shock with imperfect labor markets. They also show that countries gain in the short-run because benefits from trade arise instantaneously after a fall in trade costs.

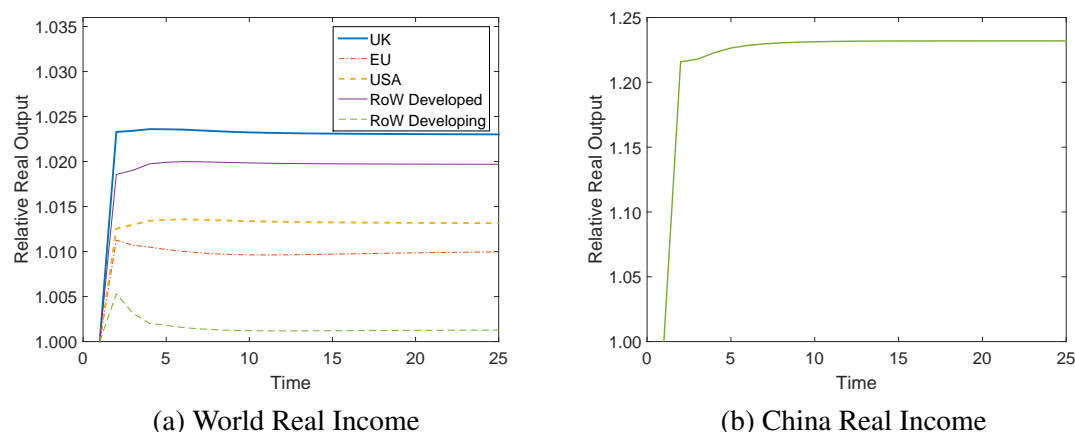


Figure 1: World Real Income

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Real income relative to the initial steady state equilibrium.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

fierce import competition from China. Hence, the overshooting of wages accruing to EU workers (together with the fact that consumers have access to cheaper goods) excessively benefits this “country” in the short-run. Other countries such as the UK and the US exhibit an initial jump in real income (2.33% and 1.25%, respectively) and then experience a mild income increase followed by a moderate decrease. This is so because the overshooting of wages accruing to workers is mild or non-existent, generating gains that can be lower in the short-run.

Overshooting of nominal wages in a sector generally occurs when the amount of labor used in the final steady state is large relative to its initial equilibrium value. If this is the case, many jobs will have to be created after the shock, and hence, many workers and firms need to be “attracted” to the sector. This implies an overshooting of job surplus immediately after the shock, and hence, in wages.³² The undershooting of wages tends to be less pronounced and it is more difficult to be observed as job destruction can take place faster than job creation.³³ Hence, real income overshooting takes place in countries such as the EU because the number of workers initially in sectors that benefit from more Chinese trade (experiencing overshooting of wages) is sufficiently high, while

³²This overshooting also increases the production cost in the sector and help to keep markets clear in the short-run.

³³In addition, because the overshooting of wages happens more frequently, and this implies higher costs that are passed-through prices, the price indexes will generally decrease over time until the new steady is reached. This is the case for the US and for the UK, for example.

in countries like the US this is not the case.

Countries experience different levels of income changes. These levels depend on how the shock changes comparative advantages around the globe and on countries' consumption share (μ in the model) in each sector. For example, after the shock, China's comparative advantages tend to increase for manufacturing goods, especially in Low-Tech manufacturing. This implies that China will be able to export more goods at cheaper prices. If a country has a significant amount of resources allocated to the production of Low-Tech manufacturing products in the initial equilibrium, it will be hurt more severely by China. This seems to be the case for the RoW Developing, i.e., those with the smallest gain in real income.

The effects are not only heterogeneous across countries but also across sectors within countries, as shown in Figures 2a and 2b, which plot the adjustment in real wages in the UK and in the US, respectively. The only sector that experiences a fall in real wages is the Low-Tech Manufacturing one. The competition from Chinese imports is so severe in this area that the positive effects arising from cheaper Chinese goods are not sufficient to offset the negative effects associated with a fall in demand for UK/US goods. The falls in wages can be as high as 1.7% in the US and 0.8% in the UK. It is also interesting to note that real wages drop and then continue to fall before improving slightly. The rise is mainly because price indexes decrease over time in both countries (and also because conditions in the sector improve slightly over time).

Figures 3a and 3b display unemployment by sector in the UK and in the US. Initially, there is a rise in unemployment in the manufacturing sectors (especially in the Low-Tech and High-Tech in the UK and in all manufacturing in the US), followed by another jump downwards (mainly in Low-Tech manufacturing). This pattern occurs because after the initial shock, a mass of jobs is destroyed in these sectors. Then, in the next period, unemployed workers start to move toward sectors in which conditions are relatively better (Energy and Others and Mid-Tech Manufacturing in the UK; Services and Energy and Others in the US).³⁴ The Services sector is almost neutral in terms of labor force change in both countries. Labor moves toward the Energy and Others sector for two reasons. First, in the GGDC dataset countries such as the UK and the US have a comparative

³⁴Figures B.1a and B.1b in the Appendix, which present the relative size of the labor force in each sector following the trade shock, show more clearly which sectors grow or shrink relative to the initial size of the labor force.

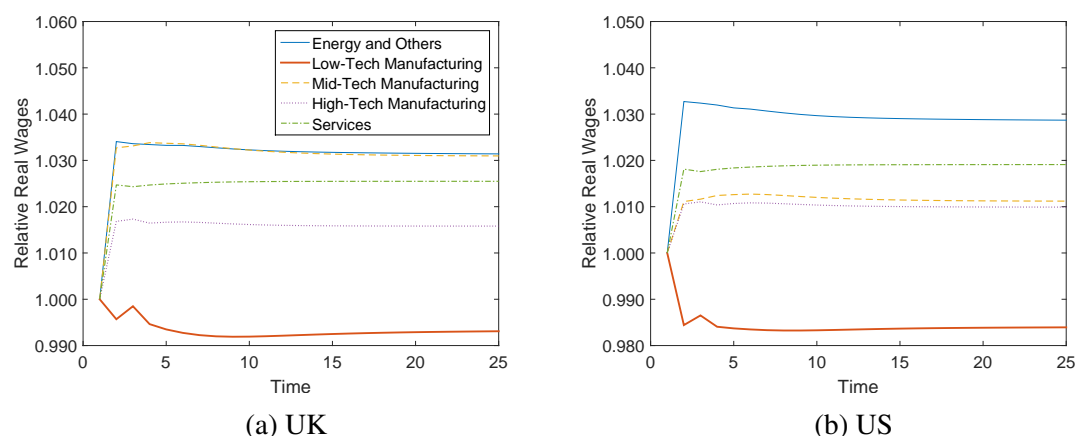


Figure 2: Relative Real Wages per Sector in the UK and in the US

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Legend in panel (a) is valid for both panels.

advantage in this sector (see Table B.2).³⁵ Second, China has a high expenditure share in this sector compared to other countries. So, as China rises, countries with higher comparative advantages in Energy and Others, including the UK and the US, benefit by sending more goods to China.

An additional interesting point is illustrated in Figure B.2a in the Appendix. Wage inequality, the ratio of the maximum to the minimum wage in the UK, falls after the trade shock. In import competing sectors, the least productive (worst paid) jobs are the ones that are destroyed, implying that the intra-sector gap between the minimum and the maximum wages will close.³⁶ In the exporting sectors, it is possible that the opposite takes place, i.e., the gap between the minimum and the maximum wage may be widening, as lower productive jobs can now exist in this sector due to a rise in demand. Overall, the first effect is the dominant one in the UK, bringing wage inequality down.³⁷ The fall in wage inequality is small, however.

³⁵Considering the way this database is constructed, one can infer that this may also reflect that goods in these industries are cheaper.

³⁶This result is common to some models with endogenous job destruction. After a “bad” technology shock in a sector, the least paid jobs are destroyed. This will tend to increase overall productivity in any country following an increase in import competition. Moreover, this will always decrease wage inequality within an industry but does not generate clear predictions regarding country overall wage inequality in a multi-sector case.

³⁷Wage inequality falls considering also another measure, the ratio between the maximum wage and the unemployment benefit (see Figure B.2b in the Appendix).

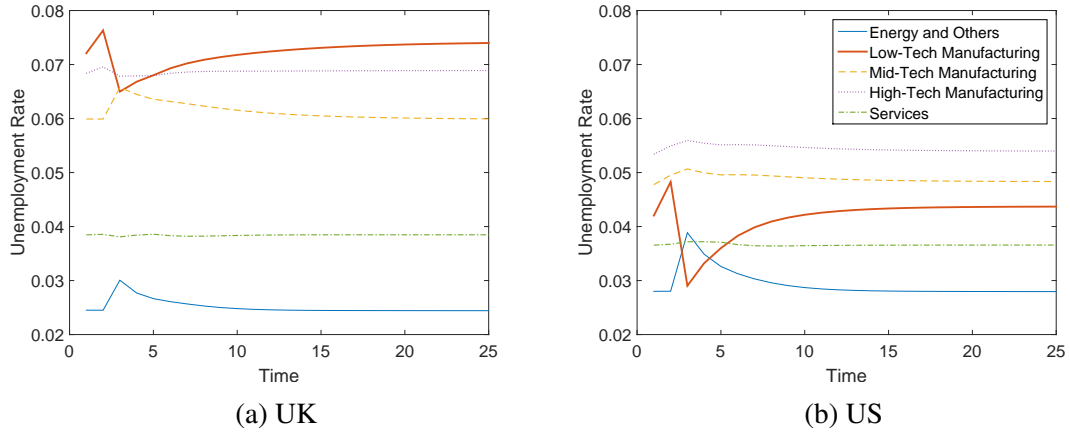


Figure 3: Unemployment Rate per Sector in the UK and in the US

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Legend in panel (b) is valid for both panels.

3.2.2 Robustness

I also verify the robustness of my results to changes in parameters values. With the exception of the new value of λ , taken from the Costinot, Donaldson, and Komunjer (2012) preferred specification, all the other new parameter values are taken from previous estimates not used in my main exercise. In my robustness exercises, I consider only the aggregate effects by country and the effects by sector in the UK only.

For example, reducing labor mobility frictions across sectors (using $\zeta = 31.25$ from Table 2, column 1) indicates that real income levels increase both in the transition and in the new steady state (see Figure B.4 in the Appendix), but the difference is small. The number of workers that decide to relocate to other sectors is also higher. This exercise suggests that reducing labor mobility frictions allows countries to benefit more from trade shocks.

Increasing the trade elasticity λ to 6.453, as in Costinot, Donaldson, and Komunjer (2012), reduces overall income gains, as countries benefit less from differences in comparative advantages around the world following the shock (see Figure B.5).

An increase in job destruction (setting $\rho = 0.0674$ from Table 1, column 1) does not change the aggregate results considerably (see Figure B.6). However, unemployment levels are extremely high at every point in time (including the initial steady state), and the reallocation of workers across sectors is slightly different.

4 Micro Implications of the Model

The previous counterfactual results show that all countries gain from more trade with China. However, workers in the low-tech manufacturing sector experience a fall in real wages and a rise in unemployment levels following the emergence of China. This occurs because in this sector the levels of import competition are strong, and hence, workers suffer the negative effects from a fall in demand for goods produced domestically. In this particular case, the negative effects generated by more import exposure to Chinese products outweighs the positive effects from a fall in consumption prices.

The negative *relative* effects (across sectors) of Chinese imports on workers outside China can be seen in Figures 4a and 4b, that plot changes in real wages and unemployment rates, respectively, on changes in Chinese import exposure in a country-sector pair (as well as a linear fit weighted by employment size in the country-sector in the initial steady state). Figure 4a shows a negative correlation of -0.66 between changes in wages and changes in Chinese import competition (both changes calculated across steady states), and Figure 4b presents a positive correlation of 0.73 between changes in unemployment rates (considering the initial steady state and the period immediately after the trade shock) and changes in imports from China (calculated across steady states).

In this section, I test three micro implications of my model using detailed employer-employee micro-data. I test whether more Chinese import competition: i) decrease worker's earnings (Figure 4a); ii) increase worker's number of years spent out of employment (Figure 4b); or iii) has a stronger impact on low-paid workers. The last effect is related to the pattern of job destruction in my model, i.e., when a sector receives a bad shock (such as high import competition from China) the low-paid (low-productivity) jobs are destroyed.

Autor, Dorn, and Hanson (2013) and Autor, Dorn, Hanson, and Song (2014) study the impact of the rise of China on workers in the US and find that more Chinese import competition negatively affected some manufacturing industries, reducing their employment level. More imports from China also reduced manufacturing worker's earnings. In this section, I build on the latter paper to investigate how UK workers are affected by more import competition from China. Quantitative trade exercises usually focus on the US, but as a very large and rich country, I find it useful to test the predictions of my model on a smaller and more open economy, the UK. Drawing on detailed UK data also

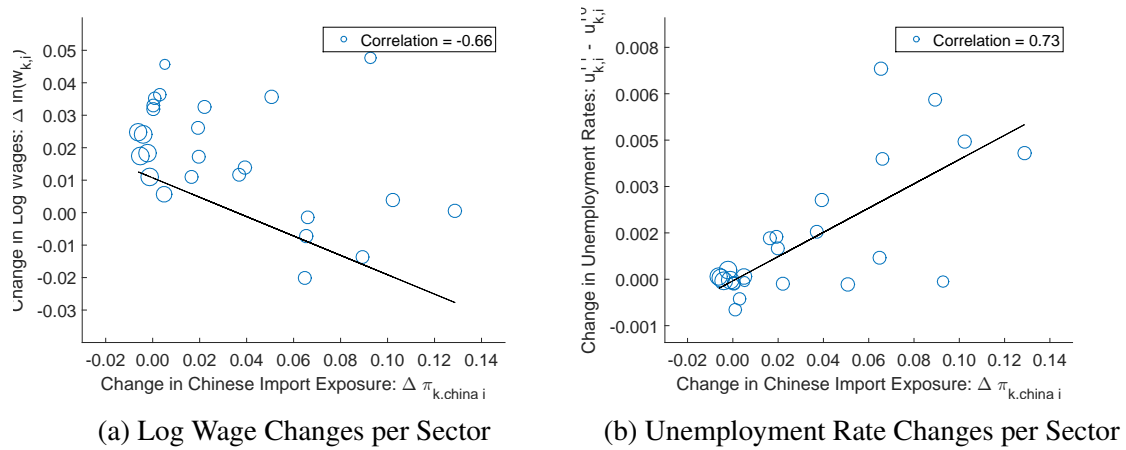


Figure 4: Counterfactual Correlations

NOTES: Panels (a) and (b) plot changes in real wages and unemployment rates, respectively, on changes in Chinese import exposure in a country-sector pair (as well as a linear fit weighted by employment size in the country-sector in the initial steady state) following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Changes in wages and changes in Chinese import competition are calculated across steady states. Changes in unemployment rates consider the initial steady state and the period immediately after the trade shock. Correlation = -0.66 in panel (a); Correlation = 0.73 in panel (B).

allows me to investigate outcomes not previously analysed by [Autor, Dorn, Hanson, and Song \(2014\)](#), such as hourly earnings. In the rest of the section I describe the data used in my reduced form analysis. I then present my empirical strategy and the results obtained by testing the partial-equilibrium implications of the model.

4.1 Empirical Strategy

I use a combination of a series of rich data sources in my analysis. At the worker level, my main dataset is the Annual Survey of Hours and Earnings (ASHE). It is an administrative dataset containing one per cent of all workers and the sample is based on the last 2 digits of the National Insurance Number (equivalent to the social security number in the US) every year since 1997.³⁸ ASHE is a panel dataset and allowed me to extract information on individuals' earnings and employment history.

To measure UK exposure to China, I use the same import penetration measure derived in my model ($\pi_{k,oi}$), which is the value of imports from a particular country divided by UK total expenditure on all goods:

³⁸Information is given considering only a reference period, usually some point in April, and includes weekly and hourly earnings, as well as the main industry of activity of the workplace. While limited in terms of personal characteristics compared to other surveys, the responses in ASHE are considered to be more accurate, because they are provided by employers rather than from the employees themselves. ASHE covers neither the self-employed nor individuals without payment in the reference period.

$$\text{Chinese Import Exposure} \equiv \frac{Imports_{chi}}{Expenditure},$$

where expenditure equals total imports plus total UK sales (shipments) minus exports. I construct this measure by combining the Business Structure Database (sales per industry) and the UN COMTRADE database (imports and exports). More details about these databases can be found in the Appendix. I consider only China, i.e., I do not include Hong-Kong and Macao in my import exposure measure.³⁹

Data on sales, exports and imports are at the 4-digit industry-level (ISIC3) and are expressed in real terms (2005 thousand of GBP) deflated by the most disaggregated Producer Price Index (PPI) provided by ONS (4-digit SIC for local production and 2-digit SIC for imports and exports).⁴⁰

Table C.1 in the Appendix shows the import exposure measure in the tradable sectors at the 2-digit ISIC3 industry level (agriculture, mining and manufacturing). The highest levels of import exposure occurred in the low-tech manufacturing sectors. Figure C.1 indicates a negative relationship between changes in $\ln(\text{employment})$ and changes in $\frac{Imports_{chi}}{Expenditure}$ from 2000 to 2007 at the 4-digit industry level.⁴¹ The fact that employment falls more in industries more affected by an import shock from China is closely related to my counterfactual results of Section 3.

My identification is motivated by Autor, Dorn, Hanson, and Song (2014). I observe workers' industry of activity in 2000 and compute its change in import exposure up to 2007. Under a certain level of mobility frictions between sectors (an assumption in my model), import shocks to the workers' initial industry should affect his/her employment and earnings history from 2001 onwards, as workers can spend more time looking for a job in the sector and/or will observe a fall in earnings while employed. My basic estimation equation is:

$$y^{lk01/07} = y^{lk97/00} + \tilde{\beta}_1 \Delta_{00/07} \frac{Imports_{chi}^{lk}}{Expenditure^{lk}} + \tilde{\beta}_2' Z^{lk} + \epsilon^{lk}.$$

The outcomes I analyze are represented by $y^{lk97/00}$, which will be one of four possi-

³⁹My results in the next subsection do not change substantially if I include these two Special Administrative Regions.

⁴⁰Imports and exports deflators are available in two categories: European Union and Non-European Union flows.

⁴¹All my import penetration measures (considering changes or levels) are winsorised at the top 99% and at the bottom 1%.

ble variables for employee l working in industry k (in 2000) in the period 2001 to 2007: i) Total Working Years - the number of years employed; ii) log of Average Weekly Earnings; iii) log of Average Hourly Earnings; and iv) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings.⁴² All earnings measures are in real terms (2005 as the base year) and winsorised at the top 99% and at the bottom 1%, and all regressions consider only workers between 17 and 59 years old in the initial period.

The change in import exposure from China between 2000 and 2007 in the worker's industry of activity in 2000 is given by $\Delta_{00/07} \frac{Imports_{chi}^{lk}}{Expenditure^{lk}}$. The measure is industry specific. The indexes emphasize it corresponds to worker l 's initial industry k .

I select 2001 as my reference point for workers' outcomes because China joined the WTO at the end of this same year. China's trade liberalization was a gradual process that started earlier, but to gain access China had to commit to several measures to further liberalize trade, such as the reduction of importing duties. China's entry into WTO also meant that restrictive importing quotas imposed by the European Union (mainly in textiles and apparel) would be lifted. Finally, the entry of China into the WTO also implied a considerable reduction in uncertainty for Chinese exporters. [Handley and Limao \(2013\)](#) show that this reduction in uncertainty in the US indeed contributed to China's export boom to the US after the WTO accession.⁴³

The error term, ε^{lk} , represents unobserved components that affect workers' outcomes of interest. This term might be correlated with contemporaneous labor demand shocks in the UK. To identify the "real China effect" in the UK labor market caused by productivity gains in China (or falling trade barriers between the two countries), I adopt an instrumental variable (IV) strategy similar to [Bloom, Draca, and Van Reenen \(2011\)](#). My IV is given by:

$$IV_{chi} = \frac{Imports_{chi}^{lk97}}{Expenditure^{lk97}} \Delta_{00/07} IE_{chi, world}.$$

To capture the supply driven Chinese effect I instrument using an interaction be-

⁴²Average annual earnings is equal to Average Weekly Earnings multiplied by 52, the number of weeks in a year.

⁴³Even though tariffs were largely unchanged after 2001, China joining the trading club led the US to implement the permanent most favored nation (MFN) status in the following year, which ended the annual threat to impose high tariffs on Chinese goods. China was not subject to such annual reviews in Europe. On the other hand, China's negotiations with the EU were completed later than with the US and much closer to its accession (2000-2001).

tween two components. The first one is the industry import exposure to China in 1997 ($\frac{Imports_{chi}^{1k97}}{Expenditure^{1k97}}$ - time invariant). I normalize this measure by the overall exogenous change in Chinese import shares (Chinese imports divided by total imports) in the world (excluding the UK and considering all tradable industries)⁴⁴ between 2000 and 2007. The identification assumption is that Chinese exports after 2000 were stronger in industries in which China had higher levels of import exposure to China in 1997. The instrument will suffer from reverse causality if trade with China and/or UK production in 1997 are affected by any type of anticipation of post 2000 shocks. To try to mitigate some of these endogeneity concerns, I add a series of additional controls in my regressions, and I also construct two different instruments and analyze the robustness of my results to these alternative IV's - see Subsection 4.3 below.

The vector Z^{1k} contains individual and industry controls, depending on each regression specification. All my regressions include average hourly earnings, average weekly earnings and average time employed between 1997 and 2000. Controlling for these lagged variables mitigates the concern that I am only picking up worker-level heterogeneity associated with changes in Chinese imports. I am interested to see how individuals with similar pre-period characteristics (including previous earnings and labor force attachment) working in industries that are affected differently by China performed between 2001 and 2007 in terms of employment and earnings.

I control for some worker's characteristics, in particular age and sex. ASHE does not provide information on individuals' education. To compare individuals with similar educational backgrounds and working in similar jobs, I control for occupation fixed effects at the 4-digit level. I also control for whether the individual was a part-time worker or a full-time worker in 2000.

I am interested in comparing individuals in similar industries. To accomplish this I control for several industry characteristics. I use real (log) industry sales, industry employment level, and real (log) industry exports to China in 2000. To rule out that Chinese imports are simply capturing a general increase in the trend of UK imports, I also control for the change in import exposure to China and the rest of the world between 1997 and 1999 and for industry import exposure from the rest of the world in 2000, all at the 4-digit level. I include a very broad measure of outsourcing in 2000: the share of input costs in the output value at the 2-digit industry level. This value is obtained from

⁴⁴This is simply a normalization as this component is constant.

UK input-output tables. I also control for previous trends in employment by including pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry).

To compare industries with similar levels of technologies, I also include R&D intensity (investment in R&D normalised by value added), real purchase of computer services and real investment in machinery at the 4-digit industry level in 2000. These variables are available at the firm level in the ARD, which I then aggregate to a 4-digit industry average using sample weights.

4.2 Validation of the Results

I start by testing whether more Chinese imports decreased earnings and/or time out of employment. Table 5 presents my main empirical findings. In all the panels, the first column is a simple OLS, and the remaining columns are estimated by IV and using a different set of controls. In particular, I add the lagged dependent variables to all columns (excluding them only makes the results stronger). “Worker Controls” in columns 3 and 5 represent all the individual-level characteristics described previously, while “Industry Controls” in columns 4 and 5 encompass the industry-level ones.

Table 5 shows that individuals working in industries more exposed to Chinese imports suffered more negative effects than those who were in industries with a lower exposure. Each one of the four panels A, B, C and D represent a different dependent variable: Log of total earnings, total working year, log of average weekly earnings and log of average hourly earnings, respectively (panels A, C and D exclude individuals with zero years of employment - see table notes for further details and mean value of dependent variable in the full sample). In the first column, which presents the OLS results, one can observe that the coefficients are negative and significant. The IV estimation in column 2 increases the absolute value of the coefficients, indicating that my OLS estimates in column 1 are biased toward zero, possibly because labor demand shocks in the UK are positively correlated with imports from China in this simpler specification without other controls. My first stages are strong, as indicated by the Kleibergen-Paap statistics (significant at all reasonable levels) in the lower part of the panels. When I control for worker’s characteristics in column 3, the coefficients fall but remain significant. This fall is mainly due to the addition of the 4-digit occupation fixed effects. Controlling for industry charac-

teristics in column 4 also decreases the coefficients relative to column 2. In column 5, the most demanding specification that includes the full set of controls, the coefficients are smaller but remain significant at standard levels, the exception being the coefficient in Panel B.

In column 5, Panel A indicates a negative effect of imports from China on Total Earnings (defined as the log of the sum of annual earnings between 2001 and 2007). With the help of Table C.2 in the Appendix, comparing a worker initially employed in an industry at the 90th percentile of Chinese import exposure ($\Delta_{00/07} \frac{Imports_{chi}^{lk}}{Expenditure^{lk}} = 0.079$) with a worker employed in an initial industry at the median of Chinese exposure ($\Delta_{00/07} \frac{Imports_{chi}^{lk}}{Expenditure^{lk}} = 0.007$), column 5 shows that an employee in the 90th percentile observed his Total Earnings fall by 4.11% = $100 * (-0.572) * (0.079 - 0.007)$ more than an employee at the median.

In Panel B, one can see that Chinese import exposure decreases the number of years spent on employment (Total Working Years) between 2001 and 2007. In column 4 of this same panel, a worker initially employed in an industry at the 90th percentile of Chinese import exposure spent 0.14 = $(-2.005) * (0.079 - 0.007)$ more years without a job when compared to a worker at the median. The only non-significant result in the table is the one in column 5 of the same panel.

Panel C presents the effects on Average Weekly Earnings (defined as the log average of weekly earnings between 2001 and 2007 considering only the years that the individual was employed). Comparing individuals initially employed in industries at the 90th and at the median of Chinese import exposure, column 5 shows that the individual in the highly affected industry earned 2.25% = $100 * (-0.313) * (0.079 - 0.007)$ less when compared to a worker at the median.

Panel D shows the effects on Hourly Earnings (defined as log average hourly earnings between 2001 and 2007 considering only the years that the individual was employed). Comparing the same two groups of workers (90th percentile and median workers), column 5 shows that workers at the 90th percentile earned 1.58% = $100 * (-0.220) * (0.079 - 0.007)$ less. Considering the results presented in Panel B, one can conclude that Chinese exposure had a greater impact on weekly earnings. This suggests that workers may be working fewer hours in industries exposed to more Chinese imports.

In sum, Table 5 indicates that more import exposure to China in a sector significantly decreases the time spent in employment and real average earnings in relative terms across

sectors). This validates some of the partial-equilibrium effects predicted by the model (see Figures 4a and 4b).

I now study the effect of Chinese imports on distinct groups of workers in terms of earnings in the pre-period (1997-2000). I use this as a proxy for the skill level of workers, assuming that a low wage implies a low skill level. A rise in import penetration should have a greater impact on the low-paid workers, especially in terms of employment as predicted by the model.

My strategy consists of adding an interaction of the change in Chinese import exposure (2000-2007) with average hourly earnings between 1997 and 2000 ($\bar{H}E_{97/00}$). If low-paid workers are more affected in terms of employment and earnings, the coefficient of this interaction should be positive.

Table 6 presents the results. All the columns are estimated using the IV and including the full set of controls. In column 2, which considers the effects on Total Working Years, the positive coefficient of the interaction indicate that low-paid workers are more affected by China in terms of employment, validating this other implication of the model. The effects on earnings (columns 1, 3 and 4) do not show any clear pattern, and the coefficients are not statistically significant. This suggests heterogeneous effects of Chinese imports on the unemployment rates of individual workers, not on their wages conditional on having a job.

4.3 Empirical Robustness

In this subsection, I verify whether the micro implications of my model are robust to different specifications. I also test the implications of the model using BSD firm-level data.

4.3.1 Alternative IV's

I make use of another instrument that builds on Bloom, Draca, and Van Reenen (2011). The instrument uses information on pre-period quotas imposed on Chinese products in textiles and apparel industries (see the Appendix for a more detailed description of the IV). Table C.3 shows that the results are qualitatively similar to the ones in Subsection 4.2, giving further support to the implications of my model.

The second alternative IV that I construct is a shift-share type of instrument similar

Table 5: Employment and Earnings

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
Panel A					
	Total Earnings				
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.849*** (0.287)	-1.224*** (0.314)	-0.804*** (0.240)	-1.040*** (0.338)	-0.572** (0.282)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		42.504*** (8.700)	37.586*** (7.37)	41.109*** (9.120)	36.881*** (7.532)
KP F Stat		23.867	26.009	20.319	23.974
Observations	23433	23428	23427	22800	22799
Panel B					
	Total Working Years				
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-2.003*** (0.646)	-2.639*** (0.908)	-2.086** (0.886)	-2.005* (1.030)	-1.459 (1.043)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		42.441*** (8.855)	37.574*** (7.514)	41.256*** (9.094)	37.162*** (7.57)
KP F Stat		22.97	25.007	20.582	24.099
Observations	24888	24882	24881	24195	24194
Panel C					
	Average Weekly Earnings				
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.422** (0.178)	-0.775*** (0.179)	-0.499*** (0.150)	-0.648*** (0.178)	-0.313** (0.130)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		42.504*** (8.700)	37.586*** (7.37)	41.109*** (9.120)	36.881*** (7.532)
KP F Stat		23.867	26.009	20.319	23.974
Observations	23433	23428	23427	22800	22799
Panel D					
	Average Hourly Earnings				
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.343** (0.142)	-0.566*** (0.175)	-0.459*** (0.138)	-0.376** (0.173)	-0.220** (0.112)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		42.505*** (8.704)	37.598*** (7.373)	41.085*** (9.132)	36.846*** (7.542)
KP F Stat		23.845	26.006	20.242	23.87
Observations	23418	23413	23412	22785	22784
$\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $Working_{97/00}$	Yes	Yes	Yes	Yes	Yes
Worker Controls	No	No	Yes	No	Yes
Industry Controls	No	No	No	Yes	Yes
$N_{clusters}$	66	66	66	61	61

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee i working in industry j (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]. Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]; Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($Working_{97/00}$) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, IV_{chi} , is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneous Effects

	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
	Total Earnings	Total Working Years	Average Weekly Earnings	Average Hourly Earnings
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-1.715 (1.142)	-8.504*** (3.059)	-0.422 (0.704)	0.279 (0.548)
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure} * \overline{HE}_{97/00}$	0.580 (0.601)	3.596** (1.547)	0.056 (0.383)	-0.253 (0.306)
$\overline{HE}_{97/00}$	0.407*** (0.044)	0.186** (0.089)	0.375*** (0.023)	0.647*** (0.027)
<u>1st Stage(s) Statistics</u>				
IV_{chi}	42.477*** (11.257)	43.314*** (11.267)	42.477*** (11.257)	42.475*** (11.281)
$IV_{chi} * \overline{HE}_{97/00}$	39.269*** (7.646)	39.968*** (7.499)	39.269*** (7.646)	39.234*** (7.647)
KP F Stat	12.467	12.507	12.467	12.42
Observations	22799	24194	22799	22784
$\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $\overline{Working}_{97/00}$	Yes	Yes	Yes	Yes
Worker Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
$N_{clusters}$	61	61	61	61

NOTES: Each column represents a different dependent variable. The last three columns exclude individuals with zero years of employment from 2001 to 2007. All columns estimated by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($Working_{97/00}$) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) from 1997 to 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, IV_{chi} , is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. I also instrument for the interactions above using this same instrument interacted with average hourly earnings. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

to the one employed by [Autor, Dorn, Hanson, and Song \(2014\)](#). It is given by:

$$\tilde{IV}_{chi} = \frac{Imports_{chi}^{lk97}}{Expenditure^{lk97}} \Delta_{00/07} IE_{chi,world}^{l\bar{j}}$$

where $\Delta_{00/07} IE_{chi,world}^{l\bar{j}}$ is the change in Chinese import exposure (defined as imports divided by expenditure) in the world (excluding the UK) between 2000 and 2007 in the worker's initial 2-digit ISIC3 industry.⁴⁵ This change in imports is interacted with 1997 Chinese import exposure in the workers' 4-digit initial industry of employment, $\frac{Imports_{chi}^{lk97}}{Expenditure^{lk97}}$. This instrument does not rely solely on pre-existing conditions, and hence, will not satisfy the exclusion restriction if there are demand or technology shocks that shift Chinese exports and are common to all countries in the world. For example, the growth of Chinese imports around the world may only reflect that many countries chose to diminish employment in low-tech labor-intensive sectors in which China had a comparative advantage, and China simply "filled the gap" in these markets. Table C.4 indicates that the qualitative predictions of my model are generally robust to this alternative IV. For example, comparing the same two groups of workers (90th percentile and median workers), Panel D, column 5, shows that workers at the 90th percentile earned 4.45% = 100 * (−0.618) * (0.079 − 0.007) less, and the coefficient is statically significant at 1% level (standard error of 0.169).⁴⁶

4.3.2 Alternative Specification

To compare my UK results with those of the US from [Autor, Dorn, Hanson, and Song \(2014\)](#), I perform an exercise in which I use a specification more similar to theirs.⁴⁷ My estimation equation is now given by:

$$w^{lk01/07} / w^{lk97/00} = \tilde{\beta}_1 \frac{\Delta_{00/07} Imports_{chi}^{lk}}{Expenditure_{00}^{lk}} + \tilde{\beta}_2' Z^{lk} + \varepsilon^{lk}.$$

First, I consider in my sample only individuals employed in all four years between 1997 and 2000 to study only workers with high labor force attachment in the pre-period, as in [Autor, Dorn, Hanson, and Song \(2014\)](#). Second, I use a different measure of Chi-

⁴⁵This measure is constructed using the WIOD database described previously.

⁴⁶Although this second IV hinges on stronger identification assumptions, this specification also allows me to add levels of Chinese exposure in 2000 as a control - see columns 4 and 5 of Table C.4.

⁴⁷See equation 5 and table 1 in their paper.

nese import exposure, which is now defined as the change in Chinese imports between 2000 and 2007 divided by the expenditure in the UK in 2000 at the 4-digit ISIC3 level in the worker's initial industry of employment in 2000, $\frac{\Delta_{00/07} Imports_{chi}^{lk}}{Expenditure_{00}^{lk}}$. The IV strategy used is the same one from my main results in Table 5, as well as the set of controls Z^{lk} .

The results are displayed in the Appendix, Table C.5. In this specification the dependent variable ($w^{lk01/07}/w^{lk97/00}$) is one of four possible outcomes. In Panel A, the dependent variable is defined as total earnings (not log earnings) between 2001 and 2007 divided by average annual earnings between 1997 and 2000 (Normalised Total Earnings). In Panel B, Total Working Years is the total number of working years between 2001 and 2007. In Panel C, Normalised Average Weekly Earnings is equal to average weekly earnings between 2001 and 2007 divided by average weekly earnings between 1997 and 2000. In Panel D, Normalised Average Hourly Earnings is equal to average hourly earnings between 2001 and 2007 divided by average hourly earnings between 1997 and 2000.

The outcomes in Panel A are comparable to the ones in Autor, Dorn, Hanson, and Song (2014). *From this point forward, I compare the same groups of workers as they do (75th vs 25th percentiles of Chinese import exposure).* In column 5 the coefficient of 2.641 implies that comparing an individual initially employed in an industry at the 75th percentile of the Chinese import exposure measure ($\frac{\Delta_{00/07} Imports_{chi}^{lk}}{Expenditure_{00}^{lk}} = 0.026$) to one at the 25th percentile ($\frac{\Delta_{00/07} Imports_{chi}^{lk}}{Expenditure_{00}^{lk}} = 0.002$), the implied differential in earnings is 6.33% = $100 * (-2.641) * (0.026 - 0.002)$ of the worker's initial earnings. Comparing the same two groups of workers in the US, Autor et al. find a value of 45.8% for a 16-year period (between 1992 and 2007). When I divide both coefficients by the number of years used in each analysis (7 and 16), the effects in the UK and in the US are 0.90% and 2.86%, respectively. This comparison is interesting as it corroborates my counterfactual results that indicate that US workers in low-tech manufacturing are also more affected by Chinese imports than employees in the UK in terms of real earnings.

My results show that employment effects in the UK are strong, whereas Autor et al. find almost no effect for the US. In Panel B of Table C.5, column 5, comparing the same two groups of workers (75th vs 25th percentiles), the implied differential in the number of years spent out of employment is $0.06 = (-2.486) * (0.026 - 0.002)$, i.e., 0.71 more months out of employment. In Panel C, the results do not indicate a clear effect on Normalised Average Weekly Earnings, as the coefficients are not significant

and switch signs occasionally. Panel D, however, shows a strong significant effect on Normalised Average Hourly Earnings, an outcome not analysed by Autor et al. The earnings differential between a worker at the 75th percentile and one at the 25th is 0.82% of initial hourly earnings.

Hence, the comparisons between the US and the UK indicate that the earnings effect is stronger in the US, while the employment effect is stronger in the UK. This may be an indication that wages are more flexible in the US than in the UK.

4.3.3 Firm-Level Data

In the Appendix, I additionally demonstrate using the BSD firm-level dataset (Table C.6) that plants in industries that faced more Chinese import exposure shut down more frequently and/or reduce their size following an import penetration shock. This implies that the partial-equilibrium effects predicted by my model are robust to firm's outcomes as well.

5 Conclusion

In this paper, I study how countries responded to the recent rise of Chinese trade. I build a tractable dynamic trade model that delivers simple expressions and incorporates several features that are important when studying the welfare impact of trade shocks, namely, imperfect labor markets, job heterogeneity and partial mobility frictions across sectors. I structurally estimate the model using country-sector level data to quantify both the losses associated with labor market adjustments and the gains to consumers generated by cheaper Chinese goods. My counterfactuals show that a fall in trade barriers between China and the world benefits all countries not only in the new steady state but also along the transition period. In import competing sectors, however, workers bear a costly transition, experiencing lower wages and a rise in unemployment.

I also carry out an empirical analysis using UK employer-employee panel data to validate the micro implications of my model. Consistent with my model predictions, I find that employees in sectors highly affected by Chinese imports spent more time out of employment and experienced a drop in earnings when compared to workers in less affected sectors between 2001 (the year China joined the WTO) and 2007 (the year before the Great Recession). I also find that low-paid workers are more affected by

Chinese import exposure.

The results raise important policy questions. The first point is that even facing a fierce competitor such as China brings benefits to developed economies, implying that any policy that aims to restrict trade in the name of more protection for workers should be reconsidered. The trade shock, however, generate winners and losers in the labor market. Hence, it *may* be welfare improving finding a way to compensate the losing individuals, and let the adjustment take place without any type of intervention that hinders trade.

The reader should bear in mind that the gains stemming from trade calculated in my counterfactuals are likely to be lower bounds, because many other GDP per capita improving channels associated with trade such as access to cheaper inputs, immigration, increases in R&D intensity, and vertical production chains, to cite just a few, are not considered in my analysis.

Finally, my tractable theoretical framework allows for studying other questions that were beyond the scope of this paper. For example, it is possible to analyze local implications of foreign labor market policies (minimum wage implementation, change in unemployment benefits and creation/destruction of unions that change workers' bargaining power).

References

- ARKOLAKIS, C., A. COSTINOT, AND A. RODRIGUEZ-CLARE (2012): "New Trade Models, Same Old Gains?," *American Economic Review*, 102(1), 94–130.
- ARTUC, E., S. CHAUDHURI, AND J. MCLAREN (2008): "Delay and dynamics in labor market adjustment: Simulation results," *Journal of International Economics, Elsevier*, 75(1), 1–13.
- (2010): "Trade Shocks and Labor Adjustment: A Structural Empirical Approach," *American Economic Review*, 100(3), 1008–45.
- AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6), 2121–68.
- AUTOR, D. H., D. DORN, G. H. HANSON, AND J. SONG (2014): "Trade Adjustment: Worker-Level Evidence," *The Quarterly Journal of Economics*, 129(4), 1799–1860.
- BERNARD, A. B., J. B. JENSEN, AND P. K. SCHOTT (2006): "Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants," *Journal of International Economics*, 68(1), 219–237.
- BLOOM, N., M. DRACA, AND J. VAN REENEN (2011): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," CEP Discussion Papers dp1000, Centre for Economic Performance, LSE.

- BLOOM, N., P. ROMER, S. TERRY, AND J. V. REENEN (2014): “Trapped Factors and China’s Impact on Global Growth,” CEP Discussion Papers dp1261, Centre for Economic Performance, LSE.
- BOROWCZYK-MARTINS, D., G. JOLIVET, AND F. POSTEL-VINAY (2013): “Accounting For Endogeneity in Matching Function Estimation,” *Review of Economic Dynamics*, 16(3), 440–451.
- CALIENDO, L., M. DVORKIN, AND F. PARRO (2015): “The Impact of Trade on Labor Market Dynamics,” NBER Working Papers 21149, National Bureau of Economic Research, Inc.
- COSAR, A. K., N. GUNER, AND J. TYBOUT (2013): “Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy,” IZA Discussion Papers 7718, Institute for the Study of Labor (IZA).
- COSTA, F., J. GARRED, AND J. P. PESSOA (2014): “Winners and Losers from a Commodities-for-Manufactures Trade Boom,” CEP Discussion Papers CEPDP1269, CEP.
- COSTINOT, A., D. DONALDSON, AND I. KOMUNJER (2012): “What Goods Do Countries Trade? A Quantitative Exploration of Ricardo’s Ideas,” *Review of Economic Studies*, 79(2), 581–608.
- DAUTH, W., S. FINDEISEN, AND J. SUEDEKUM (2012): “The Rise of the East and the Far East: German Labor Markets and Trade Integration,” IZA Discussion Papers 6685, Institute for the Study of Labor (IZA).
- DAVIS, S. J., AND J. C. HALTIWANGER (1992): “Gross Job Creation, Gross Job Destruction, and Employment Reallocation,” *The Quarterly Journal of Economics*, 107(3), 819–63.
- DI GIOVANNI, J., A. A. LEVCHENKO, AND J. ZHANG (2014): “The Global Welfare Impact of China: Trade Integration and Technological Change,” *American Economic Journal: Macroeconomics*, 6(3), 153–83.
- DIX-CARNEIRO, R. (2014): “Trade Liberalization and Labor Market Dynamics,” *Econometrica*, 82(3), 825–885.
- DONALDSON, D. (2010): “Railroads of the Raj: Estimating the Impact of Transportation Infrastructure,” NBER Working Papers 16487, National Bureau of Economic Research, Inc.
- DUBIN, J. A. (1985): *Consumer Durable Choice and the Demand for Electricity*, Contributions to Economic Analysis. North-Holland.
- EATON, J., AND S. KORTUM (2002): “Technology, Geography, and Trade,” *Econometrica*, 70(5), 1741–1779.
- FELBERMAYR, G., G. IMPULLITTI, AND J. PRAT (2014): “Firm Dynamics and Residual Inequality in Open Economies,” Discussion paper.
- FELBERMAYR, G., J. PRAT, AND H.-J. SCHMERER (2011): “Trade and unemployment: What do the data say?,” *European Economic Review*, 55(6), 741–758.
- FELBERMAYR, G. J., M. LARCH, AND W. LECHTHALER (2013): “Unemployment in an Interdependent World,” *American Economic Journal: Economic Policy*, 5(1), 262–301.
- FILHO, N. A. M., AND M.-A. MUENDLER (2007): “Labor Reallocation in Response to Trade Reform,” CESifo Working Paper Series 1936, CESifo Group Munich.

- HANDLEY, K., AND N. LIMA (2013): "Policy Uncertainty, Trade and Welfare: Theory and Evidence for China and the U.S.," Working Paper 19376, National Bureau of Economic Research.
- HEAD, K., AND T. MAYER (2013): "Gravity Equations: Workhorse, Toolkit, and Cookbook," CEPR Discussion Papers 9322, C.E.P.R. Discussion Papers.
- HEID, B., AND M. LARCH (2012): "International Trade and Unemployment: A Quantitative Framework," CESifo Working Paper Series 4013, CESifo Group Munich.
- HELPMAN, E., O. ITSKHOKI, M.-A. MUENDLER, AND S. REDDING (2012): "Trade and Inequality: From Theory to Estimation," CEP Discussion Papers dp1138, Centre for Economic Performance, LSE.
- HELPMAN, E., O. ITSKHOKI, AND S. REDDING (2010): "Inequality and Unemployment in a Global Economy," *Econometrica*, 78(4), 1239–1283.
- INKLAAR, R., AND M. P. TIMMER (2008): "GGDC Productivity Level Database: International Comparisons of Output, Inputs and Productivity at the Industry Level," Discussion paper.
- ITSKHOKI, O., AND E. HELPMAN (2014): "Firms, Trade and Labor Market Dynamics," Mimeo, Princeton.
- KAMBOUROV, G. (2009): "Labour Market Regulations and the Sectoral Reallocation of Workers: The Case of Trade Reforms," *Review of Economic Studies*, 76(4), 1321–1358.
- KOVAK, B. K. (2013): "Regional Effects of Trade Reform: What Is the Correct Measure of Liberalization?," *American Economic Review*, 103(5), 1960–76.
- KRAUSE, M. U., AND T. A. LUBIK (2007): "The (ir)relevance of real wage rigidity in the New Keynesian model with search frictions," *Journal of Monetary Economics*, 54(3), 706–727.
- LEVCHENKO, A. A., AND J. ZHANG (2013): "The global labor market impact of emerging giants: a quantitative assessment," Discussion paper.
- LIPTON, D., J. POTERBA, J. SACHS, AND L. SUMMERS (1982): "Multiple Shooting in Rational Expectations Models," *Econometrica*, 50(5), pp. 1329–1333.
- MANOVA, K. (2008): "Credit constraints, equity market liberalizations and international trade," *Journal of International Economics*, 76(1), 33–47.
- MELITZ, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.
- MITRA, D., AND P. RANJAN (2010): "Offshoring and unemployment: The role of search frictions labor mobility," *Journal of International Economics*, 81(2), 219–229.
- MUNZI, T., AND A. SALOMAKI (1999): "Net Replacement Rates of the Unemployed. Comparisons of Various Approaches," Discussion Paper 133, European Commission.
- O'MAHONY, M., AND M. P. TIMMER (2009): "Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database*," *The Economic Journal*, 119(538), F374–F403.
- ORNELAS, E. (2012): "Preferential Trade Agreements and the Labor Market," CEP Discussion Papers dp1117, Centre for Economic Performance, LSE.

- PFAFFERMAYR, M., P. EGGER, AND A. WEBER (2007): “Sectoral adjustment of employment to shifts in outsourcing and trade: evidence from a dynamic fixed effects multinomial logit model,” *Journal of Applied Econometrics*, 22(3), 559–580.
- PISSARIDES, C. A. (2000): *Equilibrium Unemployment Theory, 2nd Edition*, vol. 1 of *MIT Press Books*. The MIT Press.
- RANJAN, P. (2012): “Trade liberalization, unemployment, and inequality with endogenous job destruction,” *International Review of Economics & Finance*, 23(C), 16–29.
- REVENGA, A. L. (1992): “Exporting Jobs? The Impact of Import Competition on Employment and Wages in U.S. Manufacturing,” *The Quarterly Journal of Economics*, 107(1), 255–84.
- SHIMER, R. (2005): “The Cyclical Behavior of Equilibrium Unemployment and Vacancies,” *American Economic Review*, 95(1), 25–49.
- STEHNER, R., G. J. DE VRIES, B. LOS, H. DIETZENBACHER, AND M. TIMMER (2014): “The World Input-Output Database: Content, Concepts and Applications,” Discussion paper.
- TRIGARI, A. (2006): “The Role of Search Frictions and Bargaining for Inflation Dynamics,” Discussion paper.
- UTAR, H. (2006): “Employment Dynamics and Import Competition,” 2006 Meeting Papers, Society for Economic Dynamics 298, Society for Economic Dynamics.
- (2011): “Adjusting to Trade Liberalization: Reallocation and Labor Market Policies,” Mimeo, University of Chicago Booth School of Business.
- VODOPIVEC, M., AND M. H. TONG (2008): “China: improving unemployment insurance,” Social Protection Discussion Papers 44779, The World Bank.

Appendix A - Theory

I provide a proof sketch for the fact that $p_{k,i}^t z_{k,i}$ must be equal across markets that produce in equilibrium (see Sub-subsection 2.1.3). First I will show that this holds in Steady State.

Consider two varieties j and j' (all the variables associated with variety j' will be identified with a “'”). Note that workers are completely mobile across varieties. Then, using equation 3 and condition 6 we can write:

$$\theta'_{k,i} q(\theta'_{k,i})(W'_{k,i} - U'_{k,i}) = \theta_{k,i} q(\theta_{k,i})(W_{k,i} - U_{k,i}). \quad (28)$$

Now, suppose that $p'_{k,i} z'_{k,i}$ and $p_{k,i} z_{k,i}$ are not equal, and without loss of generality assume that $p'_{k,i} z'_{k,i} > p_{k,i} z_{k,i}$. This implies that the surplus accruing to workers in market j' is higher than in market j ($W'_{k,i} - U'_{k,i} > W_{k,i} - U_{k,i}$), and that wages paid in market j' are also higher. Hence, for equation 28 to hold we must have that $\theta_{k,i} q(\theta_{k,i}) > \theta'_{k,i} q(\theta'_{k,i})$, which is satisfied if and only if $\theta_{k,i} > \theta'_{k,i}$.

From [Pissarides \(2000\)](#), page 38, we know that the value of posting a vacancy is increasing in $p_{k,i} z_{k,i}$ and we can also see from equation 1 that $V_{k,i}$ is decreasing in $\theta_{k,i}$. Hence, $p'_{k,i} z'_{k,i} > p_{k,i} z_{k,i}$ and $\theta_{k,i} > \theta'_{k,i}$ imply that $V'_{k,i} > V_{k,i}$. Consequently, condition 7 cannot be satisfied and no firm will post vacancies in market j . This shows that for both markets j and j' to exist in steady state the equality $p'_{k,i} z'_{k,i} = p_{k,i} z_{k,i}$ must hold.

To see that this must also hold outside the steady state, we can rewrite 28 considering the time period immediately before the steady state T :

$$\theta'^{T-1}_{k,i} q(\theta'^{T-1}_{k,i})(W'^T_{k,i} - U'^T_{k,i}) = \theta^{T-1}_{k,i} q(\theta^{T-1}_{k,i})(W^T_{k,i} - U^T_{k,i}). \quad (29)$$

Given that I showed that $p'^T_{k,i} z'_{k,i} = p^T_{k,i} z_{k,i}$ must hold in T (implying that $W'^T_{k,i} - U'^T_{k,i} = W^T_{k,i} - U^T_{k,i}$), for equation 30 to be satisfied we must have that $\theta'^{T-1}_{k,i} = \theta^{T-1}_{k,i}$. And from the firm side (using equation 1, condition 7 and the fact that $J'^T_{k,i} = J^T_{k,i}$), the following must hold:

$$p'^{T-1}_{k,i} z'_{k,i} = q(\theta'^{T-1}_{k,i}) J'^T_{k,i}(1)/\kappa(1+r) = q(\theta^{T-1}_{k,i}) J^T_{k,i}(1)/\kappa(1+r) = p^{T-1}_{k,i} z_{k,i}. \quad (30)$$

Using the same steps, we can also show that this is valid for any previous period ($T-2, T-3, \dots$). This completes the proof sketch.

Appendix B - Counterfactuals and Robustness

B.1 Parameters

Table B.1: Country-Sector Labor Shares ($\beta_{k,i}$) and Expenditure Shares ($\mu_{k,i}$)

	Agriculture	Low-Tech Manufacturing	Mid-Tech Manufacturing	High-Tech Manufacturing	Services
Panel A: $\beta_{k,i}$					
UK	0.19	0.75	0.71	0.76	0.59
EU	0.32	0.55	0.61	0.50	0.55
China	0.32	0.34	0.37	0.36	0.41
US	0.27	0.47	0.56	0.64	0.56
RoW Developed	0.13	0.44	0.54	0.52	0.52
RoW Developing	0.18	0.27	0.28	0.32	0.39
Panel B: $\mu_{k,i}$					
UK	0.02	0.06	0.05	0.08	0.79
EU	0.03	0.09	0.07	0.11	0.70
China	0.11	0.14	0.14	0.21	0.40
US	0.03	0.07	0.05	0.10	0.75
RoW Developed	0.03	0.10	0.07	0.14	0.66
RoW Developing	0.09	0.10	0.12	0.13	0.56

NOTES: Panel A shows the labor share of value added in each sector ($\beta_{k,i}$) while panel B show the expenditure share on a particular sector ($\mu_{k,i}$). Author's calculation using WIOD and WIOD - Socio Economic Accounts database. Data is originally disaggregated by country and industry-level (roughly ISIC3 2-digit).

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

Table B.2: Country-Sector Productivity Parameters: $A_{k,i}$

	Agriculture	Low-Tech Manufacturing	Mid-Tech Manufacturing	High-Tech Manufacturing	Services
UK	1.26	1.02	1.11	1.24	0.89
EU	1.84	1.22	1.54	1.42	1.27
China	2.60	2.97	2.54	2.44	2.98
US	1.79	1.38	1.23	1.20	0.94
RoW Developed	0.70	1.28	1.19	1.44	1.11
RoW Developing	2.51	2.02	2.53	1.31	2.58

NOTES: Author's calculation using GGDC database. Data is originally disaggregated by country and industry-level (roughly ISIC3 2-digit). Productivity is the inverse of the producer price index, aggregated into sector/countries using value added as weights.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

B.2 Transition

I want to find a set of value functions that is consistent with a path that converges to the new steady state. First, one can verify that my wage equation 14 holds inside and outside of steady state. Second, $V_{k,i}^t = 0$ will always hold due to the free entry condition.

I will use numerical simulations to find a transition path toward the new steady state. I am neither claiming that this is the first best path nor the unique one. I am simply finding one set of value functions compatible with a rational expectations path.

First, I use equation 3, substitute for $W_{k,i}^t(1) - U_{k,i}^t$ using the sharing rule 5 and the value of $J_{k,i}^t(1)$ from equation 1 (remember that $V_{k,i}^t = 0$) to get:

$$U_{k,i}^t = b_i + \frac{\beta_{k,i} \kappa \theta_{k,i}^t \tilde{w}_k^t}{(1 - \beta_{k,i})} + \frac{U_{k,i}^{t+1}}{1 + r}. \quad (31)$$

To find the transition path I use a type of multiple shooting algorithm that builds on Artuc, Chaudhuri, and McLaren (2010) and Lipton, Poterba, Sachs, and Summers (1982). Even though this algorithm updates *explicitly* only $U_{k,i}^t$, it implies value functions for workers and firms that are consistent with a rational expectations path (more details below).

The economy is in equilibrium at time $t=0$. My counterfactuals consider an unanticipated shock where China's productivity increase 25% and Chinese bilateral trade costs around the world decrease 25% in all sectors apart from Services at time $t=1$.

First I calculate the new steady state equilibrium as described in Subsection 2.2. Then I conjecture that the system will converge to a new steady state in a certain amount of time, say $T_{ss} = 25$ years.⁴⁸ I guess an initial vector of values $s_{k,i}^t$ for $U_{k,i}^t$ (for all countries, sectors and time $t = 1$ to time $t = T_{ss}$). This will permit me to use equations 13, 15 and 23 to solve for $R_{k,i}^1$, $\theta_{k,i}^1$ and $\tilde{w}_{k,i}^1$, noting that $L_{k,i}^1$ and $u_{k,i}^1$ are fixed at this moment.⁴⁹ Before workers move across sectors, job creation and job destruction take place and I can calculate the new number of unemployed individuals in each sector according to equation 9. Subsequently, I pin down the share of individuals attached to each sector from equation 24 (remembering that now the value function depends on time) and unemployed

⁴⁸Note that this type of non-linear systems of equations can only be guaranteed to converge asymptotically - see Lipton, Poterba, Sachs, and Summers (1982).

⁴⁹Note that assuming that 13, 15 and 23 hold outside the steady state is an approximation. I later confirm that this approximation is a reasonable one.

individuals are reallocated according to such shares.⁵⁰ I proceed to $t = 2$ and continue like this up to time T_{ss} to find a time path for $R_{k,i}^t$, $\theta_{k,i}^t$, $\tilde{w}_{k,i}^t$, $L_{k,i}^t$ and $u_{k,i}^t$. I then update values $\tilde{s}_{k,i}^t$ of $s_{k,i}^t$ using equation 31, $\tilde{s}_{k,i}^t = b_i + \frac{\beta_{k,i} \kappa \theta_{k,i}^t \tilde{w}_{k,i}^t}{(1-\beta_{k,i})} + \frac{s_{k,i}^{t+1}}{1+r}$, and use the assumption that the system is in steady state at T_{ss} , $\tilde{s}_{k,i}^{T_{ss}-1} = b_i + \frac{\beta_{k,i} \kappa \theta_{k,i}^{T_{ss}-1} \tilde{w}_{k,i}^{T_{ss}-1}}{(1-\beta_{k,i})} + \frac{s_{k,i}^{T_{ss}}}{1+r}$. I then compare $\tilde{s}_{k,i}^t$ to $s_{k,i}^t$ and if they are close enough according to my tolerance I stop. Otherwise, I restart the algorithm using my updated values. The algorithm converges quickly to a high degree of precision. Even though this algorithm updates *explicitly* only $U_{k,i}^t$, the transition path found is almost equal to one where I update other value functions as well.⁵¹

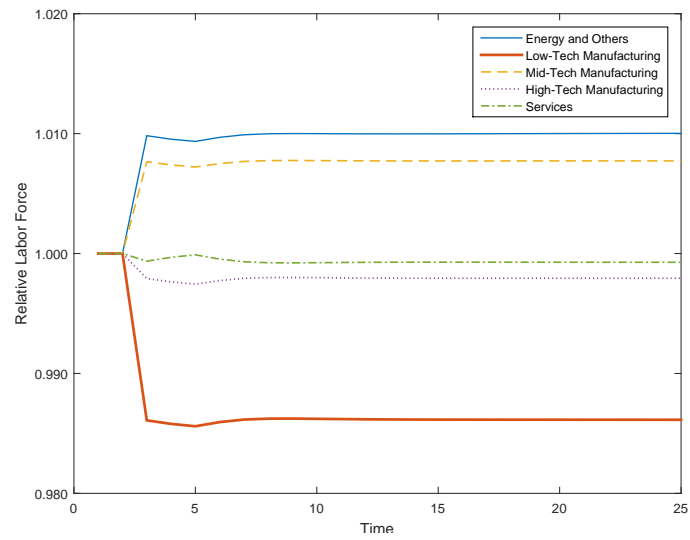
I keep T_{ss} always equal to 25, but the higher its value the closer the variables are to the new steady state counterfactual equilibrium. In my exercises, approximately 90% of the real income adjustment has already taken place by $T_{ss} = 25$.

In the algorithm there are two implicit simplifying assumptions that are not necessary to find the steady state equilibrium. First, I need to assume that after the shock the individuals willing to move (with relatively low $v_k(l)$'s) are the ones unemployed. Without this assumption, the transition would take even longer as it would be necessary that these individuals lost their jobs before moving to another sector. Second, I assume that if a variety ceases to be produced in a sector at some point in time, all matches producing that variety with an idiosyncratic productivity level above the equilibrium threshold $R_{k,i}^t$ can freely reallocate to a producing variety (pushing low productivity matches out of business and reinforcing the effect on $R_{k,i}^t$). Without this assumption, the problem would be significantly more complicated as the identity of the variety would also be a choice variable for the agents in the economy.

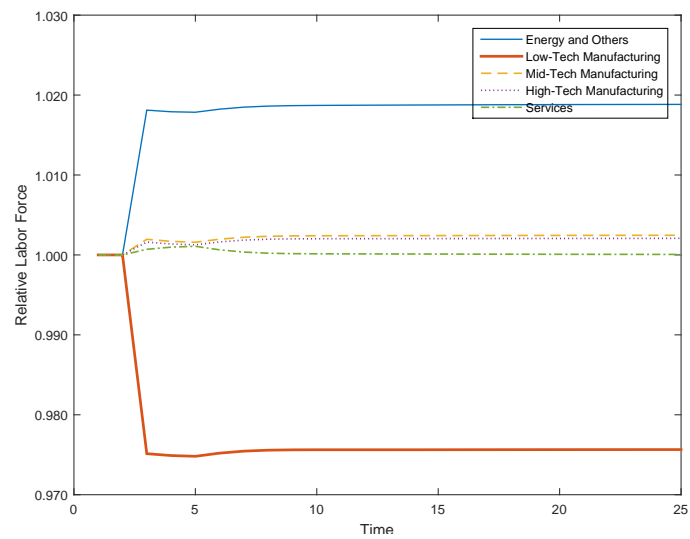
⁵⁰I am always using the Gumbel distribution to calculate the total number of individuals attached to each sector and allowing only the unemployed to move such that these shares are satisfied. A possibly more precise (and more complicated) alternative would be to find the distribution of unemployed individuals conditional on individuals previous sector choices and then find the share of individuals moving across sectors.

⁵¹To verify this I use an algorithm where I update both $J_{k,i}^t(1)$ and $U_{k,i}^t$, and $W_{k,i}^t(1)$ can then be found by the surplus sharing condition. These value functions, together with the endogenous variables are sufficient to calculate all other value functions. In this algorithm I do not assume that 13, 15 and 23 hold outside steady state, but the fact that the two transition paths (the one calculated with this algorithm and the one used in the paper) are almost indistinguishable show this was a reasonable approximation. The downside of this second algorithm is that it is sensitive to the initial guess, converging only for initial values of $J_{k,i}^t(1)$ and $U_{k,i}^t$ around the ones obtained in the final iteration of the first algorithm used in the paper.

B.3 Labor Movement and Inequality



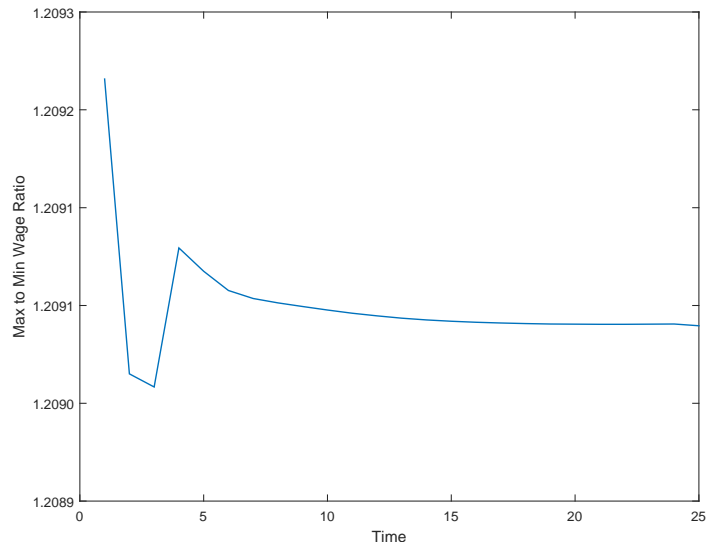
(a) UK



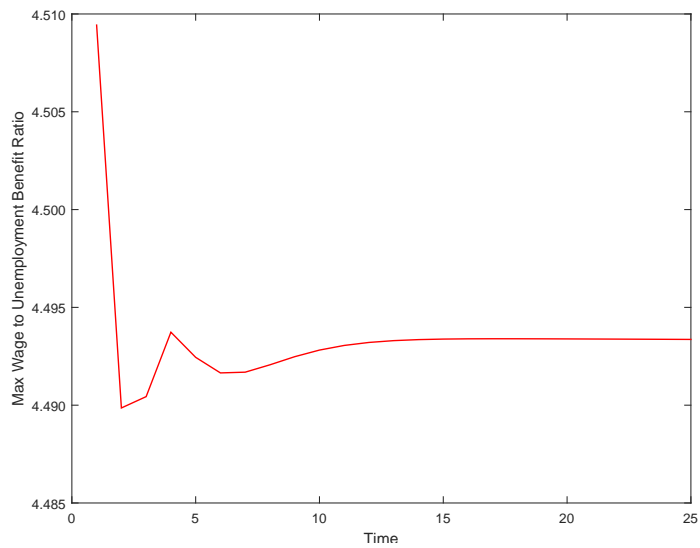
(b) US

Figure B.1: Relative Labor Force per Sector in the UK and in the US

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services.



(a) Max to Min Wage in the UK



(b) Max Wage to Unemployment Benefit in the UK

Figure B.2: UK Wage Inequality

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. In panel (a) wage inequality defined as the ratio between the maximum and the minimum wage in the UK, considering only employed individuals. In panel (b) wage inequality is defined as the ratio between the maximum wage and the value of unemployment benefit in the UK.

B.4 Welfare

In the main part of the paper I use real consumption per capita as a proxy for welfare. In the context of the model, however, a proper welfare measure should consider workers expectations about the future and their (dis)utility of moving across sectors. I present such a measure here and show its change over time in my counterfactual exercise.

$$WWelf_i^t = \sum_k L_{k,i}^t (U_{k,i}^t u_{k,i}^t + \bar{W}_{k,i}^t (1 - u_{k,i}^t) + E^t[v_k(l) | k = \max\{1, \dots, K\}]), \quad (32)$$

Where $\bar{W}_{k,i}^t$ denotes the average (over idiosyncratic productivity x) value function for a worker in sector k . I first obtain a closed form solution for this measure in steady state. To find this, I plug the wage equation 14 into 2 and subtract $J(R) = 0$ from $J(x)$ to get:

$$J_{k,i}(x) = \frac{(1 - \beta_{k,i})(1 + r)}{r + \rho} \tilde{w}_{k,i}(x - R_{k,i}). \quad (33)$$

The next step is to combine 33 and the surplus sharing rule 5 to obtain:

$$W_{k,i}(x) = U_{k,i} + \frac{(1 + r)}{r + \rho} \beta_{k,i} \tilde{w}_{k,i}(x - R_{k,i}). \quad (34)$$

Notice that $W_{k,i}(x)$ is a linear function of x , and hence, $\bar{W}_{k,i}(x) = W_{k,i}(\bar{x})$. As shown in Subsection 2.2, the average productivity in steady state is equal to $R_{k,i} + \int_{R_{k,i}}^1 s dG(s)$. From Dubin (1985) I obtain

$$E[v_k(l) | k = \max\{1, \dots, K\}] = \zeta[\gamma - \ln(\Pr[v_k(l) + U_{k,i} \geq v_{k'}(l) + U_{k',i} \text{ for } k' = 1, \dots, K])], \quad (35)$$

where γ is the Euler constant. Hence, my welfare expression is:

$$WWelf_i = \sum_k L_{k,i}^t (U_{k,i} + \frac{(1 + r)}{r + \rho} \beta_{k,i} \tilde{w}_{k,i} \int_{R_{k,i}}^1 s dG(s) + E[v_k(l) | k = \max\{1, \dots, K\}]), \quad (36)$$

where $E[v_k(l) | k = \max\{1, \dots, K\}]$ is given by 35.

To calculate this measure outside the steady state, I first back-out $U_{k,i}^t$, $u_{k,i}^t$, $\tilde{w}_{k,i}^t$,

$R_{k,i}^t$, $E^t[v_k(l)|k = \max\{1, \dots, K\}]$ and the average idiosyncratic productivity \bar{x}^t (by sector/country) directly from the transition algorithm. I approximate $W_{k,i}(x)$ by its steady state value, i.e., I consider that expression 34 is also valid outside the steady state (something that is not necessarily true). Hence, I can simply use 36 at every point in time to calculate workers' welfare (noting that I substitute $\bar{x}^t - R_{k,i}^t$ for $\int_{R_{k,i}}^1 sdG(s)$).

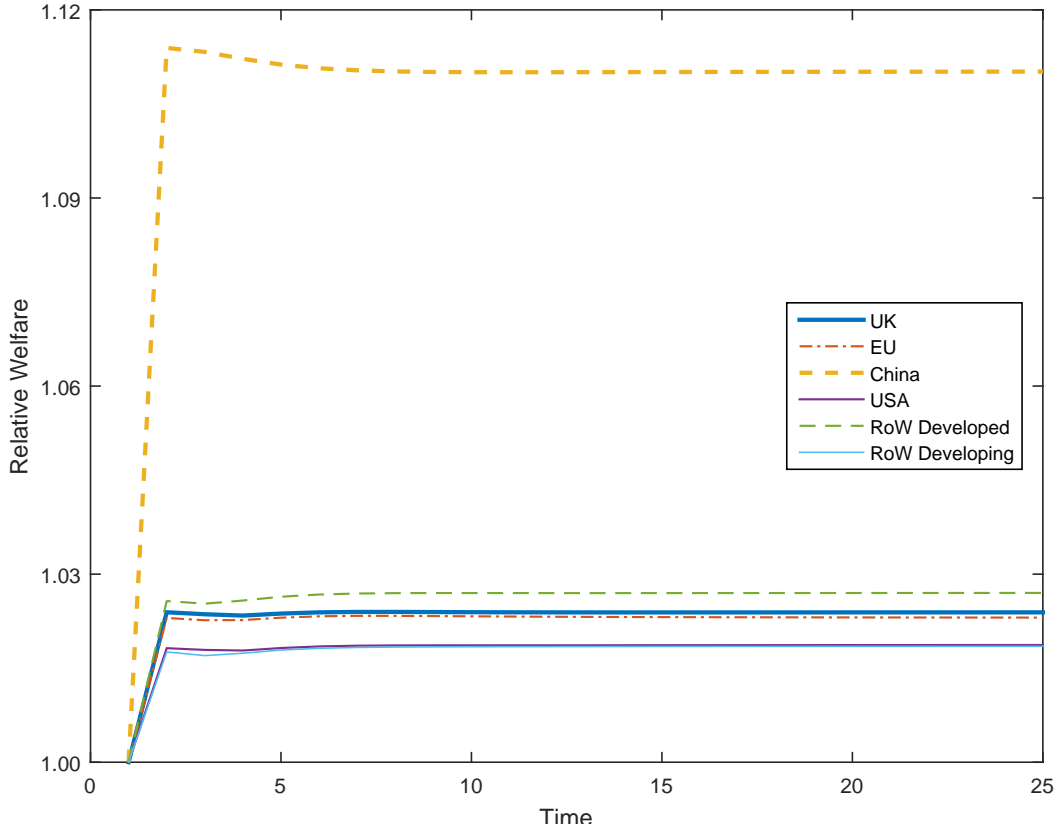


Figure B.3: World Workers' Welfare

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Welfare relative to the initial steady state equilibrium.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

Figure B.3 shows the welfare measure for all countries over time. Workers gain around the world, but the gains are different from the ones shown in Figure 1a, mainly because of the (dis)utility of workers moving across sectors. China benefits the most, followed by RoW Developed, UK, EU, USA and RoW Developing. In the new steady state China's gain is of 11.44% (compared to 23.11% of real consumption gains), while the UK and the USA gain 2.3% and 1.31 %, respectively (compared to real consumption

gains of 2.68% and 2.13%). Hence, the movement of workers across sectors is costly for these countries, especially for China. On the other hand, the EU benefits from the reallocation of workers (2.51% versus 1.02%).

B.5 Counterfactuals Robustness to Changes in Parameters

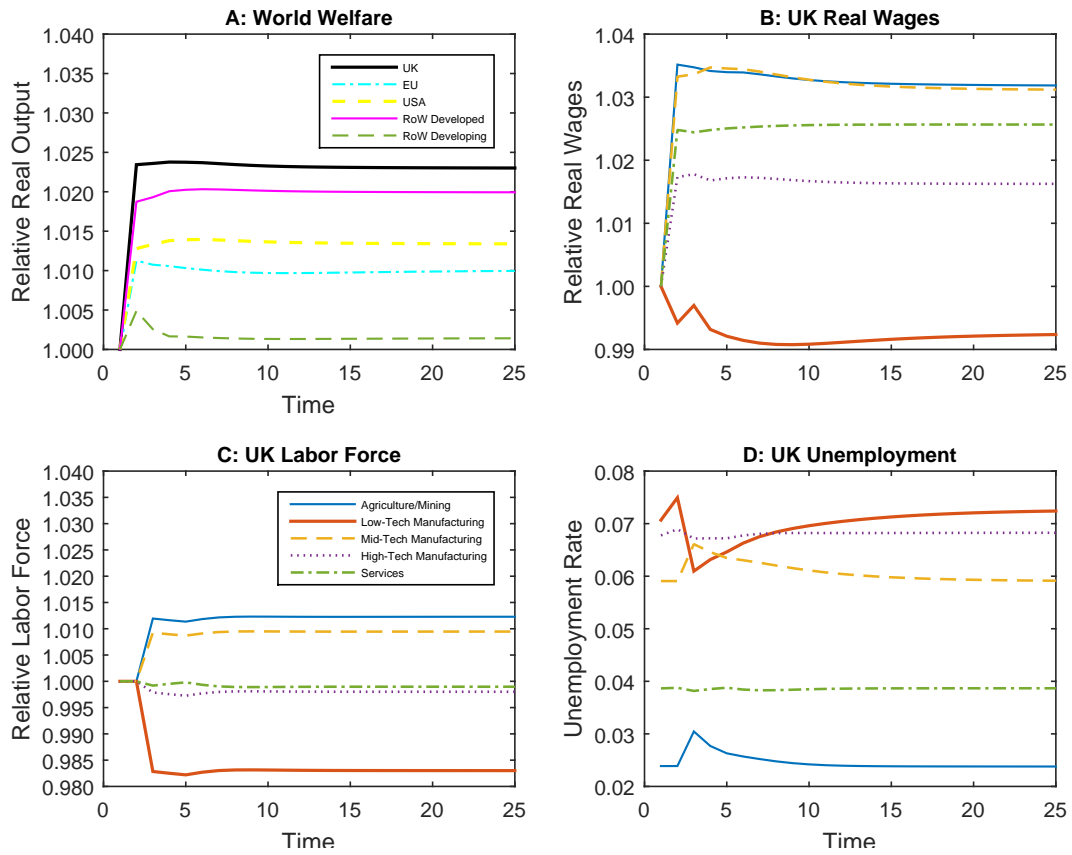


Figure B.4: Change in parameter: $\zeta = 31.25$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

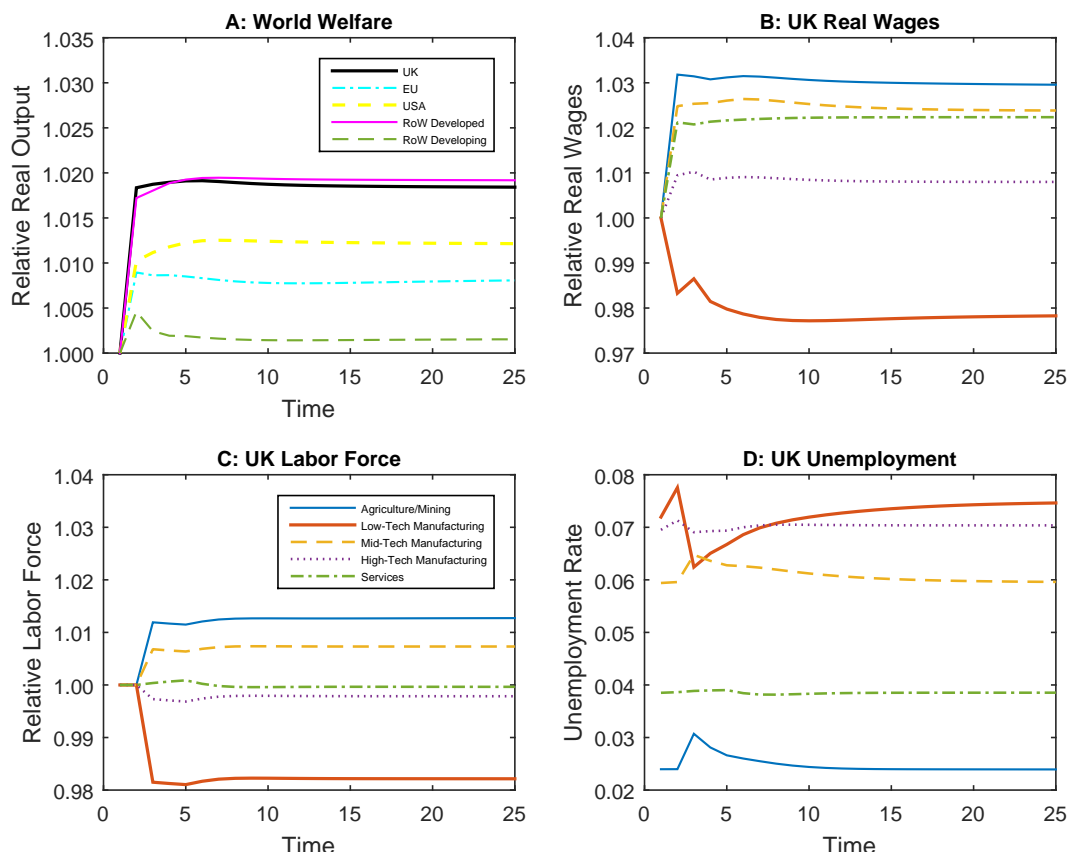


Figure B.5: Change in parameter: $\lambda = 6.453$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

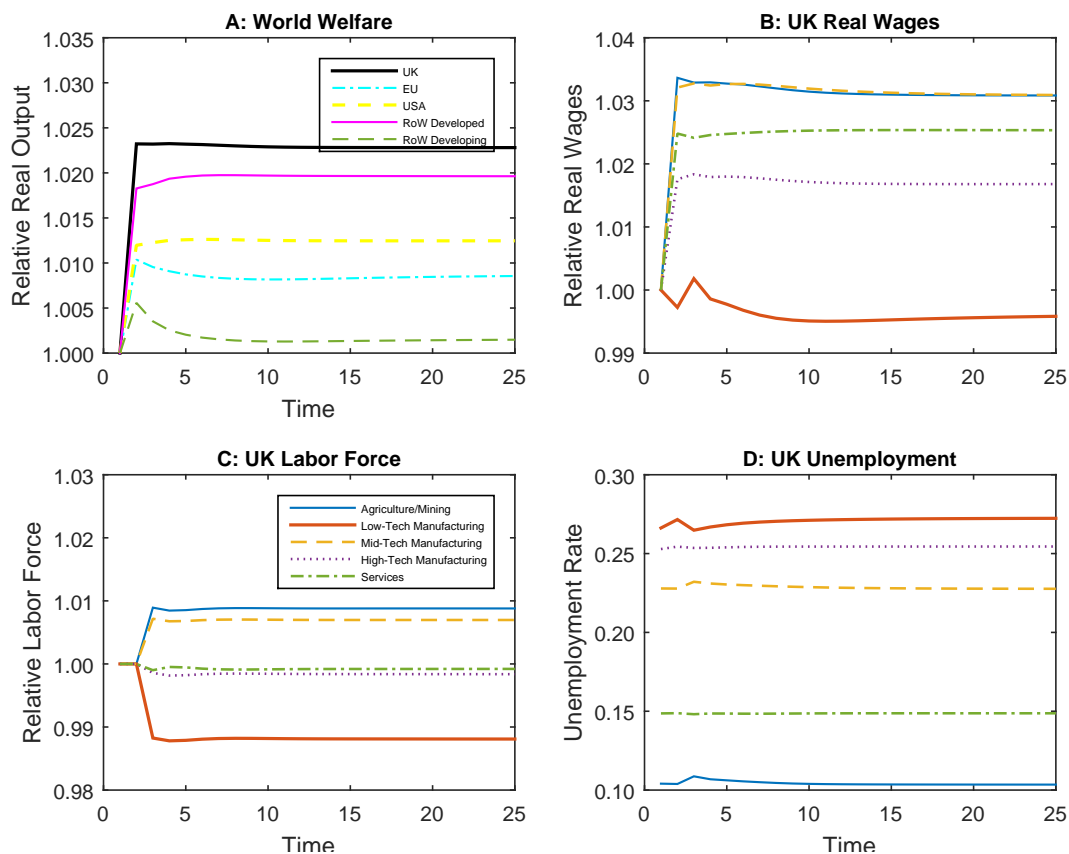


Figure B.6: Change in parameter: $\rho = 0.0674$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.

EU: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

RoW Developed: Australia, Canada, Japan, Korea (south) and Taiwan.

RoW Developing: Brazil, India, Indonesia, Mexico, Russia and Turkey.

Appendix C - Micro Implications of the Model: Data and Results

C.1 Data Sources

BSD

To calculate sales per industry, a measure used in my import penetration variable, I use the Business Structure Database (BSD). It contains information on employment, sales and industry of activity for almost all business organizations in the UK. The BSD is derived mainly from the Inter-Departmental Business Register (IDBR), which is a live register of data collected by HM Revenue and Customs via VAT and Pay As You Earn records. The IDBR data are complimented using business surveys from the Office for National Statistics (ONS). If a business is liable for VAT and/or has at least one member of staff registered for the Pay as you Earn⁵² tax collection system, then the business will appear on the IDBR (and hence in the BSD). Businesses listed on the IDBR accounted for almost 99 per cent of economic activity in the UK around 2004. Only very small businesses (such as the self-employed) were not found on the register.

ARD

I use another firm data source, the Annual Respondent Database (ARD). The ARD is a census of large businesses, and a sample of smaller ones.⁵³ The advantage of ARD is that it encompasses much more detailed information than BSD. Hence, I am able to calculate, for example, firm's labor productivity, R&D intensity, wage bill and other important information used also for the structural estimation of my model in Section 3.

UN COMTRADE

Data on exports and imports use in the validation of the micro implications of the model come from the UN COMTRADE database. It carries information on all bilateral trade flows between any given pair of countries available at the 5-digit standard international trade classification revision 3 (SITC3). To create a correspondence between this trade classification and the industry classification in ASHE, BSD and ARD (5-digit UK standard industrial classification - UK SIC) I considered a third classification: the 4-digit international standard industrial classification revision 3 (ISIC3). Both SITC3 and UK

⁵²PAYE is the system that HM Revenue and Customs uses to collect Income Tax and National Insurance contributions from employees.

⁵³For more details see <http://discover.ukdataservice.ac.uk/catalogue?sn=6644>.

SIC can be easily aggregated to ISIC3, providing a consistent classification for my analysis.

C.2 UK Import Exposure to China

Table C.1 shows which industries were affected by China between 2000 and 2007 and the size of those industries in terms of employment in 2000. The greatest increase in import penetration occurred in low-tech manufacturing sectors. Several industries that faced more Chinese competition had sizeable shares of the labor force in tradable sectors (agriculture, mining and manufacturing) in 2000. The heavily affected industries are generally linked to textiles, furniture and machinery production. The sectors that observed lower increase in import penetration are inside agriculture and mining.

Table C.1: Industry Employment and Import Exposure

Sector	$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	$(\frac{Imports_{chi}}{Expenditure})_{00}$	(Employment Share) ₀₀
Wearing Apparel	0.173	0.069	3.21%
Tanning and Dressing of Leather	0.146	0.179	0.6%
Office, Accounting and Computing Machinery	0.097	0.048	1.11%
Radio, Television and Communication Equipment	0.081	0.023	3.04%
Textiles	0.080	0.030	3.48%
Furniture and Manufacturing n.e.c.	0.071	0.063	4.97%
Electrical Machinery	0.034	0.029	4.61%
Machinery and Equipment	0.033	0.015	9.21%
Wood and Cork (except furniture)	0.030	0.010	1.86%
Basic Metals	0.029	0.004	2.40%
Fabricated Metal Products ^{*A}	0.028	0.020	5.14%
Other Non-Metallic Mineral Products	0.023	0.005	3.36%
Rubber and Plastic	0.014	0.020	5.68%
Medical, Optical and Other Instruments ^{*B}	0.009	0.016	3.61%
Paper	0.009	0.003	2.53%
Forestry and Logging	0.005	0.007	0.25%
Chemicals	0.005	0.007	6.58%
Publishing and Printing ^{*C}	0.004	0.004	8.20%
Other Transport Equipment	0.003	0.005	3.81%
Other Mining and Quarrying	0.003	0.002	0.87%
Fishing	0.003	0.001	0.28%
Motor Vehicles, Trailers and Semi-Trailers	0.002	0.000	5.18%
Mining of Coal and Lignite	0.002	0.004	0.32%
Food and Beverages	0.002	0.001	11.61%
Coke, Refined Petroleum and Nuclear Fuel	0.000	0.001	0.66%
Tobacco	0.000	0.000	0.22%
Crude Petroleum and Natural Gas	0.000	0.000	0.35%
Agriculture and Hunting	-0.000	0.004	6.86%
<i>Total</i>			<i>100%</i>

NOTES: Table considers only tradable industries (agriculture, manufacturing and mining). Changes in Chinese import penetration from 2000 to 2007, Chinese import penetration measure in 2000 and employment shares in 2000 by industry (ISIC3 2-digit). The denominator of this last measure considers only tradable industries.

^{*A} Excludes machinery and equipment.

^{*B} Includes watches and clocks.

^{*C} Includes reproduction of recorded media.

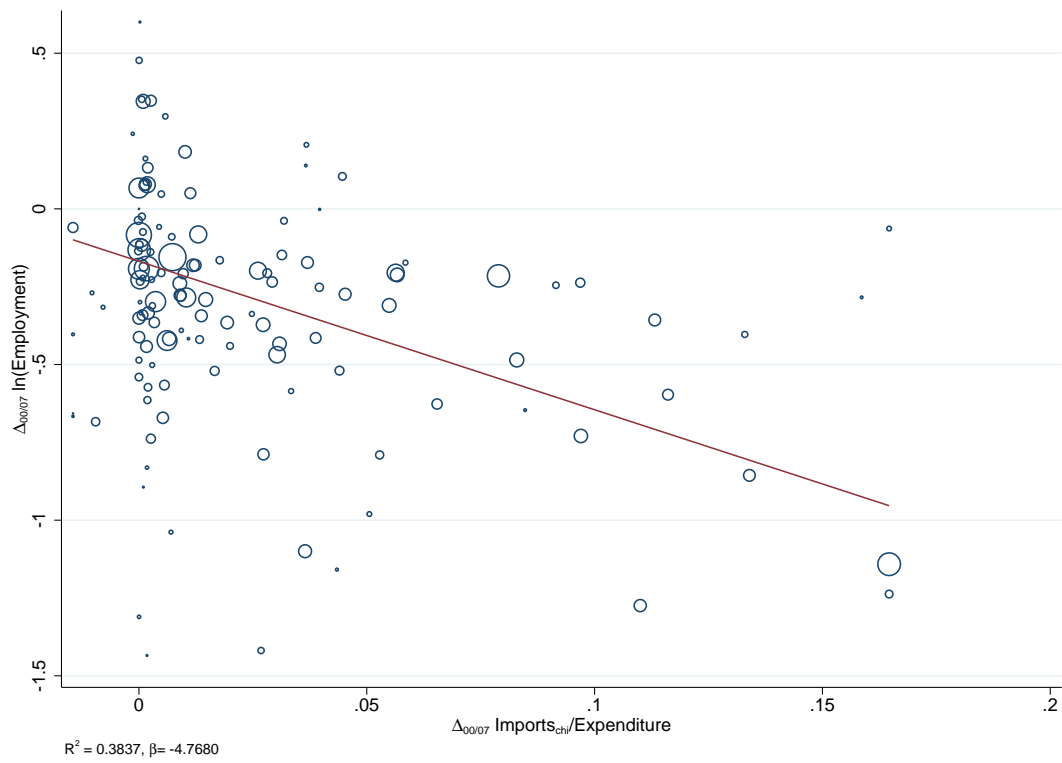


Figure C.1: Changes in industry log Employment against Chinese Import Exposure

NOTES: Figure plots changes in employment between 2000 and 2007 against changes in exposure to Chinese imports in the UK at the 4-digit ISIC3 industry level. All points (and fitted line) consider industry employment size in 2000 as weights. β represents the coefficient of the fitted line (standard error of 0.53).

C.3 Summary Statistics

Table C.2: Summary Statistics

	Average Hourly Earnings	Average Weekly Earnings	Total Earnings	Total Working Years	$\overline{HE}_{97/00}$	$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	IV_{quota}
Obs	23418	23433	23433	24888	24888	24888	24888
Mean	2.335	5.971	11.372	4.540	2.210	0.025	0.020
Std. Dev	0.467	0.537	0.829	2.124	0.456	0.038	0.099
Min	-	-	-	-	-	-0.014	0
10 th Pctile	1.791	5.341	10.227	1.000	1.659	0.000	0.000
50 th Pctile	2.281	5.984	11.510	5.000	2.180	0.007	0.000
90 th Pctile	2.957	6.600	12.271	7.000	2.798	0.079	0.000
Max	-	-	-	-	-	0.165	0.603

NOTES: Summary statistics for the full sample of individuals from years 2000 to 2007. Some statistics are omitted because of data confidentiality reasons.

C.4 Empirical Robustness

I also make use of another instrument based on [Bloom, Draca, and Van Reenen \(2011\)](#). This IV uses the idea that many Chinese products in the textile industry had importing quotas until China entered in the WTO (2001). Since these quotas were first implemented in the fifties and their phased abolition negotiations started in the eighties, it is natural to assume that they are exogenous to current demand and supply shocks in the UK. As quotas started to be liberalised, imports in these protected sectors increased significantly. To build my IV I first calculate the fraction of products⁵⁴ that were under quota restriction in a given industry k before the liberalization phase in the 2000's. The number of industries under quotas is extremely small under the ISIC3 classification⁵⁵, which makes this simple fraction a poor IV. To add more variability to my instrument, I use the average value of the quota share in the industries where each worker was between 1997 and 2000. My new IV is given by:

$$IV_{quota} = \frac{\sum_{t < 2001} quota^{ikt}}{T},$$

where T is the number of years that an individual was employed between 1997 and 2000 and $quota^{ikt}$ is the share of products that had quotas in worker's industry of activity at time t . Clearly this IV has its own issues. Even though I use workers' pre-period industry switch, this information may still reflect anticipation to China shocks. In this case my IV would not be strictly exogenous. [Bloom, Draca, and Van Reenen \(2011\)](#) claim that this anticipation effect is unlikely to have had larger effects on R&D investment as there was considerable uncertainty about quota liberalizations at that point.⁵⁶

The results are not qualitatively different from the ones in Subsection 4.2, giving further support to my findings. The size of the coefficients in Table C.3 are larger. For example, the effect on Total Working Years, column 5, implies that an individual in the

⁵⁴[Bloom, Draca, and Van Reenen \(2011\)](#) use the same idea but have a value weighted share as the instrument.

⁵⁵The 7 industries with non-zero values and respective quota measures are: 1711 Preparation and spinning of textile fibres (0.51); 1721 Manufacture of made-up textiles (0.068); 1722 Manufacture of carpets and rugs (0.087); 1723 Manufacture of cordage, rope, twine and netting (0.5); 1729 Manufacture of textiles n.e.c (0.016); 1730 Manufacture of knitted crochet fabrics (0.375); 1810 Manufacturing of wearing apparel (0.603).

⁵⁶The authors find no correlation between their quota instrument and pre-period R&D adjustments. This suggests that this anticipation effect would also be small or nonexistent regarding pre-period labor adjustments.

90th percentile of import penetration experienced 0.36 more years out of employment when compared to a median worker. The first stage statistics are slightly weaker than in Table 5, but are still significant at standard levels.

Table C.3: Employment and Earnings: Industry Quotas as IV

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
Panel A					
Total Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.849*** (0.287)	-1.900*** (0.189)	-1.263*** (0.182)	-1.760*** (0.275)	-1.372*** (0.273)
<u>1st Stage(s) Statistics</u>					
IV_{quota}		.189*** (.045)	.164*** (.044)	.193*** (.046)	.174*** (.043)
KP F Stat		17.888	13.927	17.579	16.507
Observations	23433	23433	23432	22805	22804
Panel B					
Total Working Years					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-2.003*** (0.646)	-4.713*** (0.810)	-4.667*** (0.924)	-5.093*** (1.155)	-5.010*** (1.136)
<u>1st Stage(s) Statistics</u>					
IV_{quota}		.189*** (.044)	.165*** (.044)	.193*** (.046)	.175*** (.043)
KP F Stat		18.334	13.983	17.851	16.411
Observations	24888	24888	24887	24201	24200
Panel C					
Average Weekly Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.422** (0.178)	-1.048*** (0.139)	-0.508*** (0.095)	-0.862*** (0.139)	-0.566*** (0.115)
<u>1st Stage(s) Statistics</u>					
IV_{quota}		.189*** (.045)	.164*** (.044)	.193*** (.046)	.174*** (.043)
KP F Stat		17.888	13.927	17.579	16.507
Observations	23433	23433	23432	22805	22804
Panel D					
Average Hourly Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.343** (0.142)	-0.816*** (0.196)	-0.619*** (0.159)	-0.744*** (0.198)	-0.618*** (0.169)
<u>1st Stage(s) Statistics</u>					
IV_{quota}		.189*** (.045)	.164*** (.044)	.193*** (.046)	.174*** (.043)
KP F Stat		17.874	13.936	17.565	16.502
Observations	23418	23418	23417	22790	22789
$\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $Working_{97/00}$	Yes	Yes	Yes	Yes	Yes
Worker Controls			Yes		Yes
Industry Controls II				Yes	Yes
$N_{clusters}$	66	66	66	61	61

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee i working in industry j (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]. Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]; Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($Working_{97/00}$) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, IV_{quota} , is the average value of the quota share in the industries where each worker was between 1997 and 2000. Quota share is the fraction of Chinese products that were under quota restriction in a given industry before the liberalization phase in the 2000's. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Employment and Earnings: Shift-Share IV

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
Panel A					
Total Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.849*** (0.287)	-1.376*** (0.301)	-0.974*** (0.244)	-1.475*** (0.569)	-0.930* (0.550)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		46.78*** (5.977)	43.821*** (6.568)	41.713*** (8.948)	37.676*** (8.508)
KP F Stat		61.256	44.507	21.734	19.608
Observations	23433	23433	23432	22805	22804
Panel B					
Total Working Years					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-2.003*** (0.646)	-2.884*** (0.802)	-2.618** (0.823)	-2.849 (1.799)	-2.210 (2.038)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		46.901*** (5.952)	44.08*** (6.531)	41.18*** (8.959)	37.16*** (8.587)
KP F Stat		62.085	45.559	21.13	18.727
Observations	24888	24888	24887	24201	24200
Panel C					
Average Weekly Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.422** (0.178)	-0.710*** (0.175)	-0.385*** (0.099)	-0.829*** (0.273)	-0.487** (0.224)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		46.78*** (5.977)	43.821*** (6.568)	41.713*** (8.948)	37.676*** (8.508)
KP F Stat		61.256	44.507	21.734	19.608
Observations	23433	23433	23432	22805	22804
Panel D					
Average Hourly Earnings					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-0.343** (0.142)	-0.404** (0.167)	-0.324*** (0.099)	-0.357 (0.280)	-0.296 (0.196)
<u>1st Stage(s) Statistics</u>					
IV_{chi}		46.829*** (5.974)	43.903*** (6.567)	41.72*** (8.959)	37.697*** (8.521)
KP F Stat		61.445	44.695	21.683	19.571
Observations	23418	23418	23417	22790	22789
$\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $Working_{97/00}$	Yes	Yes	Yes	Yes	Yes
Worker Controls	No	No	Yes	No	Yes
Industry Controls II	No	No	No	Yes	Yes
$N_{clusters}$	66	66	66	61	61

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee i working in industry j (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]. Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]; Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($Working_{97/00}$) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls II" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW and from China, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, IV_{chi} , is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering the worker's initial 2-digit ISIC3 industry of employment. Standard errors clustered by industry (ISIC3 - 3 digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Normalised Earnings

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
Panel A					
Normalized Total Earnings					
$\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$	-1.364 (1.669)	-4.392*** (1.184)	-2.855** (1.114)	-3.624** (1.597)	-2.461 (1.547)
1st Stage(s) Statistics					
IV_{chi}		48.028*** (7.594)	43.616*** (6.789)	45.853*** (7.649)	42.232*** (6.693)
KP F Stat		39.995	41.27	35.933	39.809
Observations	20140	20137	20136	19572	19571
Panel B					
Total Working Years					
$\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$	-2.774*** (0.979)	-4.032*** (1.004)	-3.006*** (0.951)	-3.272*** (1.081)	-2.486** (1.151)
1st Stage(s) Statistics					
IV_{chi}		47.931*** (7.707)	43.505*** (6.941)	45.807*** (7.630)	42.314*** (6.694)
KP F Stat		38.673	39.289	36.042	39.954
Observations	21412	21409	21408	20791	20790
Panel C					
Normalized Average Weekly Earnings					
$\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$	0.161 (0.206)	-0.125 (0.183)	0.010 (0.232)	0.073 (0.306)	0.183 (0.349)
1st Stage(s) Statistics					
IV_{chi}		48.028*** (7.594)	43.616*** (6.789)	45.853*** (7.649)	42.232*** (6.693)
KP F Stat		39.995	41.270	35.933	39.809
Observations	20140	20137	20136	19572	19571
Panel D					
Normalized Average Hourly Earnings					
$\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$	0.124 (0.246)	-0.266* (0.150)	-0.193 (0.140)	-0.409* (0.215)	-0.344* (0.191)
1st Stage(s) Statistics					
IV_{chi}		48.024*** (7.599)	43.637*** (6.795)	45.830*** (7.657)	42.210*** (6.702)
KP F Stat		39.939	41.240	35.828	39.668
Observations	20124	20121	20120	19556	19555
Worker Controls.	No	No	Yes	No	Yes
Industry Controls	No	No	No	Yes	Yes
$N_{clusters}$	66	66	66	61	61

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee i working in industry j (in 2000) in the period that goes from 2001 to 2007. Panel A) Normalised Total Earnings - total earnings between 2001 and 2007 divided by average annual earnings between 1997 and 2000 [mean in the full-sample = 5.85]. Panel B) Total Working Years - the number of years employed between 2001 and 2007 [mean in the full-sample = 4.58]; Panel C) Normalised Average Weekly Earnings - average weekly earnings between 2001 and 2007 divided by average weekly earnings between 1997 and 2000 [mean in the full-sample = 1.201]; Panel D) Normalised Average Hourly Earnings - average hourly earnings between 2001 and 2007 divided by average hourly earnings between 1997 and 2000 [mean in the full-sample = 1.162].; Panels C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, IV_{chi} , is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.5 Firms

Using information from the BSD I also investigate firms' outcomes that are tightly related to unemployment and earnings. My empirical approach is similar to the one presented in Subsection 4.1, but i indexes firms instead of workers. My initial time period is still 2000, but different from the worker analysis I now include new entrants in my sample, i.e., I also consider firms that entered in any year after (and including) 2001 in some specifications. I allocate to all firms the same import shock (change in import penetration 2000/2007).

My dependent variables are either: i) Activity Status, a dummy variable equals to 1 if a firm was alive in 2007 and 0 otherwise; or ii) Employment Growth, defined as change in $\ln(\text{employment})$ between 2000 and 2007 considering only surviving plants.

I focus on local units, which is generally equivalent to plant level data. My set of controls in Table C.6, "Firm Level Controls", include enterprise birth date fixed effects and a dummy for enterprise foreign ownership in the starting period. "Industry Controls" include the same variables described in the main text.

The results are strong both in the extensive and in the intensive margin of job destruction, giving further support to the partial-equilibrium effects generated by my counterfactuals. Looking at the 5th column, a 1 percentage point increase in Chinese import penetration leads to an increase of 0.96 percentage points in the probability of death of a firm and to a reduction of 2.256 percentage points in the annual employment growth between 2000 and 2007. Hence, plants shut down and/or reduce their size following an import penetration shock.

Table C.6: Firms - Local Units

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
Panel A					
Activity Status					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	-1.670*** (0.460)	-2.021*** (0.649)	-1.364*** (0.313)	-0.998* (0.570)	-0.964* (0.542)
<i>1st Stage(s) Statistics</i>					
IV_{chi}		18.233*** (2.222)	17.504*** (2.552)	14.345*** (1.976)	14.172*** (1.982)
KP F Stat		67.316	47.035	52.702	51.144
Observations	364814	363777	297002	270819	216224
Panel B					
Employment Growth					
$\Delta_{00/07} \frac{Imports_{chi}}{Expenditure}$	0.375 (0.568)	-0.335 (0.939)	-1.879*** (0.509)	-1.766*** (0.593)	-2.256*** (0.453)
<i>1st Stage(s) Statistics</i>					
IV_{chi}		17.602*** (2.822)	16.587*** (3.109)	13.358*** (2.359)	13.308*** (2.351)
KP F Stat		38.909	28.457	32.074	32.03
Observations	124083	123888	123888	73055	73055
Firm Controls	No	No	Yes	No	Yes
Industry Controls	No	No	No	Yes	Yes
$N_{clusters}$	66	66	66	62	62

NOTES: Estimations considering plant level data. Each panel represents a different dependent variable. Panel A) Activity Status, a dummy variable equals to 1 if a firm was alive in 2007 and 0 otherwise [mean in the full-sample = 0.499]; Panel B) Employment Growth, defined as change in $\ln(\text{employment})$ between 2000 and 2007 considering only surviving plants [mean in the full-sample = 1.44]. Panel B considers only surviving plants from 2000 to 2007, while Panel A considers dead and surviving plants, as well as new entrants. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration relative to plants' industry of employment in 2000 or plants' industry in its entry year if plant enters after 2000. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. "Firm Controls" include enterprise birth date fixed effects and a dummy for enterprise foreign ownership in the starting period. Instrument for change in industry Chinese import penetration, IV_{chi} , is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Robust standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1410	Claudia Olivetti Barbara Petrongolo	The Evolution of Gender Gaps in Industrialized Countries
1409	Quoc-Anh Do Kieu-Trang Nguyen Anh N. Tran	One Mandarin Benefits the Whole Clan: Hometown Favoritism in an Authoritarian Regime
1408	Caroline J. Charpentier Jan-Emmanuel De Neve Jonathan P. Roiser Tali Sharot	Models of Affective Decision-making: How do Feelings Predict Choice?
1407	Johannes Boehm Swati Dhingra John Morrow	Swimming Upstream: Input-output Linkages and the Direction of Product Adoption
1406	Felix Koenig Alan Manning Barbara Petrongolo	Reservation Wages and the Wage Flexibility Puzzle
1405	Gianluca Benigno Luca Fornaro	Stagnation Traps
1404	Brian Bell Stephen Machin	Minimum Wages and Firm Value
1403	Gene M. Grossman Elhanan Helpman Ezra Oberfield Thomas Sampson	Balanced Growth Despite Uzawa
1402	Emanuele Forlani Ralf Martin Giordano Mion Mirabelle Muûls	Unraveling Firms: Demand, Productivity and Markups Heterogeneity
1401	Holger Breinlich	The Effect of Trade Liberalization on Firm- Level Profits: An Event-Study Approach

1400	Richard V. Burkhauser Jan-Emmanuel De Neve Nattavudh Powdthavee	Top Incomes and Human Well-Being Around the World
1399	Rabah Arezki Thiemo Fetzer	On the Comparative Advantage of U.S. Manufacturing: Evidence from the Shale Gas Revolution
1398	Adriana Kocornik-Mina Thomas K.J. McDermott Guy Michaels Ferdinand Rauch	Flooded Cities
1397	Lorenzo Caliendo Giordano Mion Luca David Opromolla Esteban Rossi-Hansberg	Productivity and Organization in Portuguese Firms
1396	Richard Murphy Gill Wyness	Testing Means-Tested Aid
1395	Zack Cooper Stuart Craig Martin Gaynor John Van Reenen	The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured
1394	Hannes Schwandt Amelie Wuppermann	The Youngest Get the Pill: Misdiagnosis and the Production of Education in Germany
1393	Yatang Lin Yu Qin Zhuan Xie	International Technology Transfer and Domestic Innovation: Evidence from the High-Speed Rail Sector in China
1392	Robin Naylor Jeremy Smith Shqiponja Telhaj	Graduate Returns, Degree Class Premia and Higher Education Expansion in the UK
1391	Marc Fleurbaey Hannes Schwandt	Do People Seek To Maximize Their Subjective Well-Being?

The Centre for Economic Performance Publications Unit
Tel 020 7955 7673 Fax 020 7404 0612
Email info@cep.lse.ac.uk Web site <http://cep.lse.ac.uk>